# Upskilling the silver workforce: learning Industry 4.0 skills in purchasing and supply management

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**ABSTRACT,**

***The purchasing and supply management (PSM) sector faces rapid digital transformation due to Industry 4.0. With this transformation, organisations must upskill their aging workforce to ensure continued competitiveness. This study explores how silver workers, employees aged 50 years old and older, perceive and evaluate different learning methodologies for acquiring Industry 4.0 skills. Drawing on data from 235 professionals in the EXPERTISE project, this research assesses preferences and perceived effectiveness of e-learning, hands-on workshops, and blended learning formats. A quantitative analysis, including t-tests, ANOVA, and multiple linear regression was used to test hypotheses regarding training preferences and the moderating effects of individual factors (age, experience, and workload). Findings indicate that silver workers generally prefer hands-on and blended learning over e-learning, with training effectiveness significantly shaped by individual characteristics. Age negatively affects the perceived effectiveness of e-learning, while experience positively influences hands-on learning outcomes. Contrary to expectation, higher workload enhances the effectiveness of hands-on training. These findings highlight how individual factors shape training outcomes beyond the learning methods itself. Perceived relevance and clear communication also play key roles in training effectiveness. This study contributes to the underexplored area of upskilling older professionals in digital contexts and provides actionable insights for designing training programs that align with silver workers' needs.***

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**Keywords**
Silver workers, Industry 4.0, purchasing and supply management (PSM), learning methodologies, upskilling, training effectiveness.

# 1. INTRODUCTION: LEARNING METHODOLOGIES FOR AN AGING WORKFORCE IN PSM

Industry 4.0, also known as the fourth industrial revolution, marks a significant transformation in how companies operate and compete by leveraging advanced digital technologies. The revolution aims to integrate humans, robots, and automated systems in unique ways (Islam, 2022, p.2). This rapid digital transformation driven by Industry 4.0 technologies is reshaping the purchasing and supply management (PSM) field (Delke et al., 2023, p.1-2). This evolving environment creates the need for continuous adaptation and upskilling. PSM professionals are required to adapt quickly to increasingly digital workflows, decision-making tools, and data-driven environments (Sieber, n.d., p.2; Islam, 2022, p. 2; Li, 2024, p. 10). Industry 4.0 technologies require employees to continuously develop new competencies through virtual, online, and modular learning platforms to keep up with evolving job demands (Schiele et al., 2022, p.164). Delke et al. (2021, p.9-10) identify nine future purchasing skills as key areas for further development toward Industry 4.0, with data analytics and e-procurement technology as the most impactful skills. Both digital and physical Industry 4.0 technologies and workforce skills must grow together. Without upskilling, a company risks losing the productivity and competitive gains these technologies promise (Pedota et al., 2023, p.9-10).

The PSM workforce is aging. A significant portion of the employees in this field are now over 50 years of age (University, T. U. D., 2023, p.6-7). These individuals are often referred to as "silver workers". TU Dortmund University (2023, p.8) define silver workers as: *"All employees with an age of 50 and older and have a permanent working position in a company"*. These experienced professionals are an important asset to organisations but also face challenges, like cognitive barriers, lack of digital skills, and reduced motivation, when trying to adapt to the requirements of the digital transformation (Froehlich et al., 2023, pp. 48–49). With new digital technologies, workers cannot always rely on previous knowledge. Employees are therefore required to continuously obtain new knowledge to keep up with work expectations. Learning outcomes are, however, significantly affected by worker characteristics such as experience, age, and workload (Paloniemi, 2006, p. 442), while Industry 4.0 forces high learning demands due to complex technologies. If supported properly, silver workers can bring significant strengths that enhance the implementation of Industry 4.0 strategies within companies. Organizations should leverage the existing expertise of older professionals to strengthen digital transformation efforts (Komp-Leukkunen et al., 2022, p.48).

Empirical research on learning methodologies for teaching Industry 4.0 skills to silver workers in the PSM sector remains limited. The role of individual factors like prior digital exposure and professional experience have not been sufficiently explored in shaping learning methodologies. This gap in research risks excluding a highly experienced part of the workforce, due to unfitting training formats, from contributing to organisational innovation. If silver workers are excluded from contributing to innovation due to inadequate training methodologies, organizations risk underutilizing a highly experienced and knowledgeable segment of their workforce.

The goal of this research is to explore how silver workers in the purchasing and supply management sector perceive and evaluate different learning methodologies aimed at developing Industry 4.0 skills. This study seeks to identify which approaches align best with silver workers, by examining their preferences and the perceived effectiveness of using learning methodologies like e-learning, hands-on workshops, and blended learning. Additionally, it considers how individual characteristics, such as age, experience, and workload, may shape training outcomes. To investigate these issues, this study addresses the following research questions:

1. What are preferred and effective learning methodologies such as e-learning, hands-on workshops, and blended learning for silver workers?
2. To what extent do individual factors such as age, experience, and perceived workload predict silver workers' perceived effectiveness with different learning methodologies?

To answer these research questions, a quantitative approach was selected to systematically analyse patterns and relationships within the data. This approach allows for objective measurement of preferences and effectiveness. The study focuses exclusively on learning methodologies used by silver workers, based on the responses from participants in the EXPERTISE project survey.

The structure of this paper is as follows: section 2 reviews the literature, section 3 explains the methodology, section 4 presents the results, section 5 discusses implications, and section 6 outlines limitations and future research.

Findings show that silver workers generally prefer hands-on and blended learning over e-learning, with age, experience, and workload significantly shaping perceived effectiveness. This research contributes to closing a gap in the literature and offers practical insights for organisations aiming to implement training methodologies that are effective for silver workers.

# 2. LITERATURE: CONCEPTUAL FOUNDATIONS FOR SILVER WORKERS TRAINING IN PSM

## *2.1. Effectiveness of learning methodologies*

Professional education within the concept of Industry 4.0 must be adapted with new models for teaching and learning, with a focus on interdisciplinary skills (Kipper et al., 2021. p.2). Privitera (2023, p. 13) defines learning methodologies as the scientific study of the underlying bases of learning with the goal of describing, understanding, or improving learning across developmental stages and diverse contexts. Tikhonova et al. (2023, p. 7) identifies that the modern andragogy models applied in teaching and learning are shifting to other approaches. As their perception of learning is partly shaped by the way they were originally trained.

Within this context, the learning models that should be used for acquiring new competencies suited for professional training in Industry 4.0 are: electronic-based (e-learning), blended learning (a mixture of face-to-face and electronic-based learning), and hands-on workshops (Tikhonova et al., 2023, p.7; Benis et al., 2021, p.3).

Each approach offers different benefits and limitations, especially when considering the unique needs, preferences, and prior experiences of older employees.

Understanding how these methodologies align with silver workers' learning styles is essential for effective upskilling the silver workforce. Silver workers bring valuable experience but may also require tailored approaches that respect their prior knowledge and support their preferred learning formats. Wotschack et al. (2023, p. 248) emphasize that workers acquire skills effectively through repeated task performance and practical application. However, current upskilling initiatives in PSM are often not tailored to the specific needs of silver workers, highlighting a gap between training content and learner characteristics (EXPERTISE, 2023, p. 21; 2024, p. 27). This gap underscores the importance of the need to explore learning methodologies that are better aligned with the preferences and capacities of silver workers.

E-learning technologies offer flexibility, accessibility, and self-paced learning opportunities. It may also foster new skills, like e-literacy (Becker, 2012, p.387). However, older workers may experience challenges facing this new way of digital learning. Without proper guidance or contextual relevance, e-learning can hinder engagement and knowledge transfer among the silver workforce.

Blended learning, which integrates online and offline instruction, has been shown to be effective for adult learners with diverse needs (Deschacht et al., 2015, p.83). This approach combines the benefits of digital flexibility while providing hands-on practice, social interaction, and immediate feedback. Silver workers find this motivating and supportive (EXPERTISE, 2024, p. 30). Similarly, Ranasinghe (2024, p. 15) suggest that blended learning may offer an ideal balance in learning methods for the silver workforce. It improves effectiveness by aligning learners' responsibilities and tasks. Blended learning has also been shown to enhance engagement, accommodate diverse learning styles, and improve knowledge retention among older learners (Deschacht et al., 2015, p. 85).

Hands-on workshops represent an experiential learning model where active participation, practical application, and context-rich environments are emphasized. Wotschack et al. (2023, p.240) and EXPERTISE (2024, p. 28) highlight how this aligns closely with silver workers' preferences for practical, task-oriented training. This is due to the fact that silver workers tend to favour hands-on and visual learning approaches, requiring individualized pacing and recognition of their existing skills. Froehlich et al. (2022, p. 10) further note that older workers are more motivated when training is closely tied to real tasks and accompanied by social support, such as feedback and supervisor involvement.

Given these distinctions, it is essential to investigate which formats are most suitable for enhancing Industry 4.0 capabilities among the silver workforce. Therefore, the following hypotheses are proposed:

<u>H1:</u> Silver workers show a preference for blended learning methodologies (H1a) (which combine hands-on workshops and e-learning) as approach for acquiring Industry 4.0 skills, with a stronger preference towards hands-on workshops (H1b) over e-learning alone (H1c).

<u>H2:</u> There is a significant difference in perceived effectiveness between the three learning methodologies: e-learning, hands-on workshops, and blended learning.

### *2.2 Impact of age, experience, and workload on preferred learning methods*

To understand the influence of individual factors, it is necessary to examine how they affect preferred learning methods. More specifically for this study, the general effectiveness of learning formats is closely linked to how silver workers engage with and benefit from them, as individual characteristics such as age, experience, and workload play a significant role in shaping these outcomes.

Armstrong-Stassen et al. (2007, p.420) stress the importance of continuous and lifelong learning within organisations as one of the most effective strategies for preventing early retirement. Despite the proven value of lifelong learning for older workers, most existing training programs are designed with a younger audience in mind. Organizations should leverage the existing knowledge of older professionals to strengthen digital transformation efforts and remain productive and competitive (Ranasinghe, 2024, p.2). Ranasinghe (2024, p.10) also points out barriers for silver workers in digital learning environments. Wotschack et al. (2023, p.248) emphasize that silver workers often struggle when adapting to unfamiliar digital systems, which can hinder their learning progress and perceived effectiveness.

<u>H3a:</u> Age negatively moderates the relation between e-learning and perceived effectiveness.

In contrast, work experience has been shown to act as a driving force in learning contexts. According to Paas et al. (2003, p. 65–66), high perceived workload can negatively impact cognitive capacity, limiting an individual's ability to process and retain new information. Hatano et al. (1986, p. 7) introduces the concept of adaptive expertise, which describes experienced professionals not only perform routine tasks well, but can also flexibly solve new problems. Similarly, Paloniemi (2006, p.447) notes that experience acts as a source for competence and is helpful in further learning, particularly when training is task-specific and allows for knowledge transfer. Older workers often draw on prior expertise and absorb new knowledge. Finally, research shows that older workers participate less in training due to reduced perceived payoff, especially when nearing retirement, and limited employer attention to their training needs (Picchio, 2021, p. 3). This problem does not lay with the older employees themselves. EXPERTISE (2024, p.17) showed older employees are indeed willing to adapt, if effective communication and teamwork is provided. The report also emphasizes that experience-based learning improves both engagement and outcomes in silver workforce training.

<u>H3b:</u> Experience (years worked in PSM) positively moderates the relationship between hands-on training formats and perceived effectiveness.

While age and experience influence how older employees approach training, high workload remains a limiting factor. According to Ranasinghe (2024, p.8) organizational pressure and time scarcity reduce participation in learning activities. Similarly, Rikala et al. (2024, p.7) argue that high workloads reduce both the depth of learning and the effectiveness of training, particularly in formats requiring active participation. Finally, Ruysseveldt et al. (2010, p.12) identify that workload limits the ability to learn from, and with colleagues. While interactional and task-related learning opportunities both support the acquisition of new competencies, the overall effect of workload on workplace learning is negative.

H3c: Perceived workload negatively moderates the relationship between hands-on learning and perceived effectiveness.

Figure 1 illustrates the relationships among the hypotheses, based on the conceptual model developed using the literature.

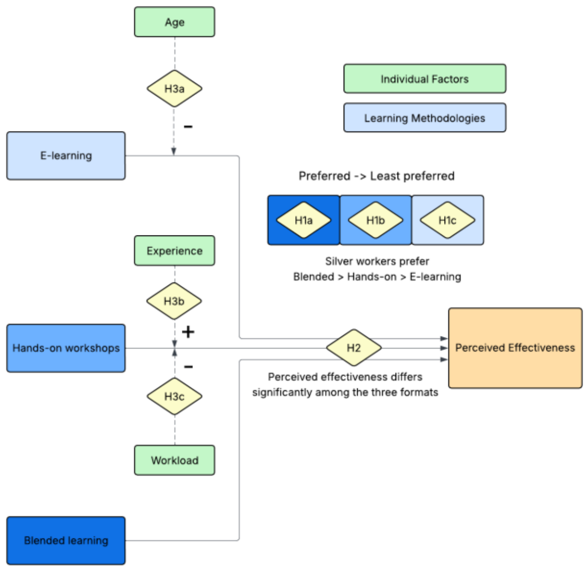


**Figure 1: Conceptual hypotheses diagram**

## 3. METHODOLOGY: ANALYTICAL APPROACH TO LEARNING EFFECTIVENESS

### *3.1 Method selection*

A quantitative research design was selected to explore silver workers' preferences for -, and perceived effectiveness of learning methodologies for acquiring Industry 4.0 skills. This approach enables objective measurement and statistical analysis of relationships between learning methodology outcomes (preference and effectiveness) and individual characteristics (age, experience, workload).

To assess the perceived effectiveness of these learning methodologies, the analysis draws theoretically from Kirkpatrick's four-level training evaluation model (1994). The model provides a structured view to assess how silver workers experience and apply different learning methodologies for acquiring new competencies. By distinguishing between immediate reactions (level 1), learning outcomes (level 2), behavioural application (level 3), and long-term results (level 4), the model supports a nuanced understanding of which methodologies are not only engaging but also lead to meaningful workplace impact. This model remains the most widely adopted framework for training assessment in professional contexts (Alsalamah et al., 2021, p. 40). Its layered approach is particularly useful for silver workers, as it captures not only immediate learning gains but also long-term behavioural outcomes (Nawaz et al., 2022, pp. 35–36).

A combination of descriptive statistics, correlation analysis, paired samples t-tests, one-way ANOVA, and multiple linear regression was applied to analyse the data. These techniques were selected to identify significant differences across groups, test hypotheses, and explore how individual characteristics moderate the relationship between training format and perceived effectiveness (Field, 2017).

### *3.2 Research sample*

This study draws from data obtained through a survey conducted by the EXPERTISE project, which focuses on the training and development of experienced professionals in PSM across Europe. The dataset includes responses from 235 participants and covers a wide range of variables related to learning preferences, training environments, and organizational practices. It also captures key demographic and professional characteristics necessary for analysing learning trends among silver workers. Table 1 provides an overview of the core demographic characteristics of the sample. These indicators help contextualize the learning preferences and perceived effectiveness outcomes.

**Table 1 – Demographics EXPERTISE dataset**

| Variable | Value / Description |
|---|---|
| Mean Age | 47.9 years |
| Silver Workers (≥ 50 y.) | 54.9% of sample |
| Mean Experience | 15.3 years |
| Gender Distribution | 66.4% male, 33.6% female |
| Full-Time Workers | 81.7% of sample |

### *3.3 Operationalization of variables*

Silver workers are identified in the dataset based on age and employment status, focusing on employees with the age of 50 years old and older with permanent contracts. The dataset provides relevant demographic and professional information such as age, gender, country of origin and workplace, education level, job title, company sector, company size (both in revenue and employee numbers), and the number of workers aged 50+ in PSM functions.

During data cleaning, columns containing irrelevant and high missing values (>50%) were removed, following standard missing-data guidelines (Osborne, 2008, pp. 39–45).

The outputs of the EXPERTISE dataset need to be quantified to be compatible for different analysis methods. The response outputs of the data set follow the Likert scale. Likert-type scales are widely used to convert qualitative survey data into quantitative measures (Norman, 2010, p.625).

### *3.4 Data analysis*

Descriptive statistics were used to summarize the key characteristics of the dataset. They define the basic aspects of a dataset, without exploring causal relationships between the variables. The descriptive statistics provide a foundation for further explanatory research by offering a clear and structured overview (Field, 2017, p.35040; Nassaji, 2015, p.129). A distinction has been made between the individual factors and the ten question categories for optimal interpretation. The descriptive statistics can be found in Appendix A. Furthermore, frequency distributions show how respondents rated each method and help summarize the data (Field, 2017, p.38).

One-way ANOVA is a suitable method to compare mean ratings across different learning methodologies to identify which are perceived most effective. This is done for all respondents and silver workers alone. One-way ANOVA tests whether there are statistically significant differences between the means of different independent groups. It does so by comparing between-group variance to within-group variance, generating an F-statistic. If F-statistic is significant, it suggests at least one group mean differs from others (Atkinson et al., 1998, p.224).

Paired samples t-tests are used to compare the mean perceived effectiveness and preference scores within the silver worker respondents. For example, paired samples t-tests assess whether silver workers rate the effectiveness of e-learning, hands-on workshops, or blended learning significantly differently. This helps identify differences in how learning methodologies are perceived.

Multiple linear regression analysis is applied to examine how individual characteristics, such as age, experience, and perceived workload, influence the perceived effectiveness of each learning methodology according to silver workers. This method allows for the testing of moderation effects as outlined in hypotheses H3a, H3b, and H3c. Multiple linear regression reveals how and to what extent individual factors shape learning outcomes, which is crucial for designing tailored training programs for silver workers in the Industry 4.0 era. As Ziglari (2017, pp. 15–16) points out, structure coefficients, which correlate each predictor with the predicted outcome, offer a clearer view of a predictor's unique contribution. By standardizing variables, beta coefficients are reported in standard deviation units, making them comparable across predictors regardless of original measurement scales (Nieminen, 2022, p. 434). In our model, this allows us to directly compare the influence of age, experience, and workload on online learning effectiveness using their standardized βs.

Correlation analysis is used to explore the relationships between continuous variables (age, experience, perceived workload) and the perceived effectiveness scores for each learning methodology (e-learning, hands-on workshops, and blended learning). Pearson's correlation coefficients identify the strength and direction of these relationships, without establishing a cause-and-effect link (Prematunga, 2012, p.195; Bewick et al, 2003, p.451).

## 4. RESULTS: IMPACT OF LEARNING METHODOLOGIES AND INDIVIDUAL FACTORS

### *4.1 Descriptive statistics*

Silver workers ranked their ideal learning format characteristics on a scale of 1-10 (1 being the worst, and 10 the best). The following key distributions are calculated for each format to understand their distributions: mean, standard deviation, skewness, and kurtosis. Table 2 presents the mean and standard deviation for perceived effectiveness for each format according to silver workers.

**Table 2 – Descriptive Statistics for Learning Preferences**

| Learning Preference | Mean | Standard Deviation |
|---|---|---|
| Pref_CustomPaths | 7.19 | 2.87 |
| Pref_HandsOn | 8.00 | 1.96 |
| Pref_Feedback | 5.42 | 2.59 |
| Pref_IndividualPace | 5.14 | 2.73 |
| Pref_Materials | 6.06 | 2.45 |
| Pref_IndependentStudy | 5.09 | 2.53 |
| Pref_PositiveAttitude | 5.34 | 2.69 |
| Pref_DemandOriented | 4.87 | 2.98 |
| Pref_InnovativeFormats | 4.20 | 2.82 |
| Pref_BenefitsAwareness | 3.69 | 2.28 |

These rankings were used to identify the most and least valued training aspects. As Table 2 shows, incorporating real-world scenarios and practical applications (hands-on workshops) received the highest average score (M = 8.00), while raising awareness about benefits of programs scored the lowest (M = 3.69). For learning environment practices, having an interactive and engaging program was ranked most important by the respondents (M = 8.35). Whilst having a cross-functional learning environment was the least valuable (M = 3.71). Additionally, having a cross generational learning environment showed high kurtosis and positive skew, indicating that only a minority rated them extremely positively, while most responses clustered towards moderate values. Regarding their organisation's training environment, respondents reported that their organisations already have a hands-on training environment (M = 3.57). While their organisations have less focus on having customized learning paths (M = 3.22).

Frequency distributions further highlight methodological preferences. These distributions show how often each rating was selected by the respondents and provide valuable insight into preferences for different training approaches. The results from preferences of learning and learning environment can be found in Figure 3 (all other results in Appendix B).

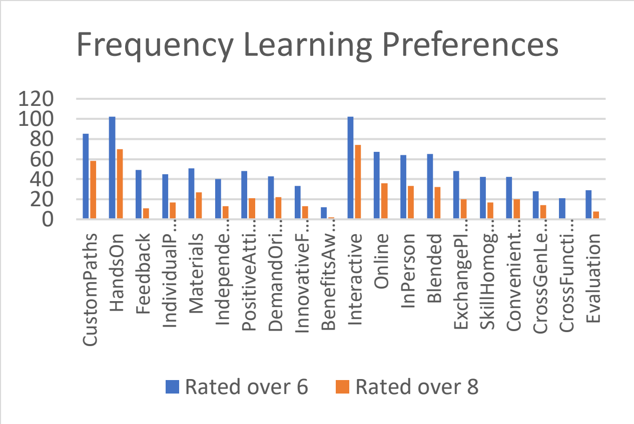


**Figure 3 – Frequency learning preferences**

Having an environment that is interactive and engaging was most valued by the silver workers, with 102 respondents rating it above 6 and 74 rating it above 8. This indicates that silver workers value training environments that involve participation and dynamic formats. Having an environment with customized training paths also scored high among the silver workers, with over half of the respondents scoring it above 6. This indicates silver workers value training formats tailored to their specific needs.

The three learning methodologies (e-learning, hands-on workshops, and blended learning) were ranked relatively high. A hands-on training formats was valued highest by silver workers, highlighting silver workers value practical and experience-based training approaches. Blended learning received consistent support with moderate scores, indicating it strikes a good balance between flexibility and engagement. Interestingly, online learning showed a split response, some respondents rated it high while others rated it very low. This implies a need for more targeted implementation. Other training formats like having an open exchange platform to communicate with colleagues, fostering a positive attitude towards new technologies and methods, and including learning materials that allow to study independently also benefit silver workers.

Silver workers favoured awareness less. This learning methods includes regular evaluation and assessment of the program, while being aware of the relevant benefits. This indicates it is viewed as supplementary rather than essential. Overall, silver workers favour collaborative and interactive training environments that emphasize practical relevance and tailored content.

## *4.2 Correlation*

A Pearson's correlation analysis was conducted to reveal underlying patterns, assess the strength, and direction of relationships between key continuous variables (Prematunga, 2012, p.195). These variables included age, gender, experience, workload, and perceived effectiveness ratings for different learning methods according to silver workers. The results are summarized in Appendix C. These findings suggest that individual factors, such as age and workload, show minimal association with perceived effectiveness. However, experience shows a moderately positively related relationships with perceived effectiveness. Preferences for learning formats also vary, with gender and workload showing differing associations with online and blended environments. Based on these patterns, a multiple regression analysis will be conducted to further explore how these individual characteristics predict perceived effectiveness.

## *4.3 Statistical analysis of learning method preferences*

To evaluate the preference of different learning methods for acquiring Industry 4.0 skills according to silver workers, a series of paired-sample t-tests and one-way ANOVA were conducted. The results can be found in Table 3 and in Appendix D.

The results indicate a significant difference in perceived effectiveness across the three learning methodologies. Paired-sample t-tests reveal that hands-on learning is significantly preferred over online-only formats, and blended learning is significantly preferred over hands-on learning. However, no significant difference was found between blended and online learning environments, suggesting that while hands-on and blended formats are generally preferred, participants did not clearly favour blended learning over online learning.

**Table 3 – Statistical comparison of learning preferences**

| ***Comparison*** | ***Test*** | ***t / F value*** | ***df*** | ***p-value*** | ***Result*** | ***Related Hypothesis*** |
|---|---|---|---|---|---|---|
| Pref_HandsOn vs. Env_Online | Paired-sample t-test | t = 6.12 | 126 | $p < 0.001$ | Significant (Hands-on preferred) | H1a: Hands-on is preferred over e-learning |
| Env_Blended vs. Pref_HandsOn | Paired-sample t-test | t = -6.39 | 126 | $p < 0.001$ | Significant (Blended preferred) | H1b: Blended learning is preferred over hands-on |
| Env_Blended vs. Env_Online | Paired-sample t-test | t = 0.220 | 126 | $p = 0.413$ | Not significant | H1c: No significant preference for blended over e-learning |
| Pref_HandsOn, Env_Online, Env_Blended | One-way ANOVA | F = 24.00 | (2, 678) | $p < 0.001$ | Significant (At least one differs) | H2: Confirms a significant difference in effectiveness across the three methods |

### *4.4 Multiple linear regression with moderators*

To test hypotheses H3a-H3c, both simple linear regression (SLR) and multiple linear regression (MLP) analyses were conducted. Simple linear regressions provide valuable insights into how individual factors influence preferences for different learning methodologies. Additionally, multiple linear regression allows for examining how moderator variables interact with learning methodologies to influence perceived effectiveness, providing a deeper understanding of conditional effects beyond simple direct relationships. The results can be seen in Table 4.

For H3a, the simple linear regression indicated no significant relationship between age and perceived effectiveness of e-learning, suggesting that age alone does not predict how effective e-learning is perceived. The multiple linear regression analysis revealed a significant negative interaction between age and e-learning, supporting the hypothesis that age moderates the relationship between e-learning and perceived effectiveness. However, the main effect of age alone was not significant, indicating that age by itself does not directly influence perceived effectiveness outside of its interaction with e-learning. This suggests that for silver workers, age affects how they experience e-learning, so training should be adjusted to fit their needs.

Regarding H3b, the simple linear regression showed no significant direct effect of experience on perceived effectiveness of hands-on learning. However, the multiple linear regression analysis found a significant positive interaction between experience and hands-on learning, indicating that experience positively moderates the perceived effectiveness of hands-on methodologies. Additionally, experience exhibited a significant positive main effect on perceived effectiveness overall, suggesting that more experienced participants tend to perceive training as more effective in general, regardless of the learning method. This means that for silver workers, having more experience generally makes training seem more useful. Those with higher experience may find hands-on learning more effective. They could benefit from real-world tasks, physical interaction and immediate application of skills.

For H3c, the simple linear regression showed no significant direct effect of workload on perceived effectiveness of hands-on learning. The multiple linear regression analysis revealed a significant positive interaction between workload and hands-on learning, which contradicts the hypothesized negative moderating effect. The main effect of workload alone was not significant, indicating that workload's influence on perceived effectiveness is primarily present in its interaction with hands-on training. This suggests that for silver workers, workload affects how hands-on learning is experienced, meaning training programs should consider workload levels when designing hands-on activities.

In addition to the hypothesized effects, exploratory analyses revealed a new significant positive effects of workload on the perceived effectiveness of e-learning. Although this finding was not originally anticipated, it indicates that higher perceived workload might be linked to higher effectiveness ratings for an e-learning format. This means that silver workers who experience a higher workload do not perceive e-learning as less valuable.

**Table 4 – Regression analysis**

| Hypothesis | Learning method | Moderator | Effect direction (β) | p-value | Significant? | Supported? |
|---|---|---|---|---|---|---|
| H3a | E-learning | Age | -0.0011 (SLR) | p = 0.859 | No | No: No effect |
| | | Age × Online | -0.009 (MLR) | p = 0.047 | Yes | Yes: Negative moderation |
| | | Age (main effect) | -0.007 (MLR) | p = 0.645 | No | Not relevant to hypothesis |
| H3b | Hands-on | Experience | +0.021 (SLR) | p = 0.206 | No | No: No effect |
| | | Experience × Hands-on | +0.009 (MLR) | p = 0.019 | Yes | Yes: Positive moderation |
| | | Experience (main effect) | +0.024 (MLR) | p < 0.001 | Yes | Experience is positively related to effectiveness overall |
| H3c | Hands-on | Workload | -0.186 (SLR) | p = 0.709 | No | No: No effect |
| | | Workload × Hands-on | +0.160 (MLR) | p = 0.049 | Yes | Yes: Direction contradicts hypothesis |
| | | Workload (main effect) | +0.207 (MLR) | p = 0.235 | No | Not relevant to hypothesis |
| New | E-learning | Workload | +2.66 (SLR) | p < 0.0001 | Yes | - |

## 5. DISCUSSION: INSIGHTS FOR SUPPORTING SILVER WORKERS IN THE DIGITAL TRANSFORMATION

### *5.1 Individual factors in learning effectiveness*

The results present a pattern in learning preferences among silver workers in the PSM sector. Hands-on workshops were more preferred than e-learning formats alone and blended learning was more preferred than hands-on formats. This finding aligns with the initial hypothesis (H1) and supports previous research emphasizing the importance of experiential, context-specific learning for older workers (EXPERTISE, 2024; Wotschack et al., 2023). Interestingly, while Ranasinghe (2024, p.11) highlighted the importance of blended learning for older workers, the statistical tests did not indicate a significantly higher preference for blended learning over e-learning. This suggests that while digital integration is generally accepted, its perceived effectiveness largely depends on its practical application within the learning context.

The findings also revealed that having an interactive and engaging environment scored the highest in overall preference. This finding highlights the importance of communication and perceived relevance. These factors are just as critical as the chosen learning methodology in engaging silver workers. Silver workers value clarity about the impact and purpose of training before fully committing to participation.

The regression analyses offer nuanced insights into how individual characteristics moderate perceived learning effectiveness among silver workers. Age showed a significant negative effect on e-learning effectiveness, supporting the view that older employees are less approving toward this format. However, the interaction effect suggests that age also shapes how e-learning is experienced, rather than uniformly lowering its effectiveness. Experience did not significantly enhance the perceived effectiveness of hands-on learning in the simple regression. However, it positively moderated the relationship in the multivariate model, indicating that more experienced workers respond more favourably to hands-on learning when other variables are considered. This challenges the assumption that experience alone directly improves perceived effectiveness with practical formats. Workload produced mixed results. While it did not have a significant main effect on perceived effectiveness overall, it positively moderated the effectiveness of hands-on learning. However, this contradicts the expected negative direction. Outside the hypotheses, exploratory analyses revealed that higher workload was positively associated with perceived effectiveness of e-learning. This suggests that employees with higher workloads may prefer practical, flexible, or hybrid training methods that fit their time constraints.

Overall, these findings question some traditional assumptions about individual factors in training preferences and highlight the need to tailor Industry 4.0 skill development programs to the diverse needs of silver workers in the PSM sector.

### *5.2 Connecting findings to learning concepts and practices*

While hands-on and blended learning formats are generally preferred over e-learning, this study reveals that training effectiveness is shaped by more than individual characteristics such as age, experience or workload. These insights challenge assumptions in existing literature and highlight the importance of practical relevance, task alignment, and communication in designing effective learning experiences for older professionals.

Firstly, this research shows that individual factors do not always enhance the perceived effectiveness of different learning methodologies among silver workers. Instead, the results suggest that the perceived effectiveness of different learning methodologies is influenced by more factors than by the individual factors alone. These results challenge earlier studies by Wotschack et al. (2023, p.240) and Froehlich et al. (2023, p.47), which emphasize the general effectiveness of hands-on, experiential learning formats for older workers.

Secondly, the effect from other factors on perceived effectiveness on the learning methodologies reinforce the need for individualized learning approaches. This is also emphasized by EXPERTISE (2024, p.17), which note that silver workers respond best to training that aligns closely with their tasks and includes clear communication. Froelich et al. (2022, p.10) similarly argue that motivation and learning intention among older workers increase when training is practical, directly relevant to their daily responsibilities, and are supported by feedback and guidance. The current findings support these insights, showing that perceived effectiveness is not only enhanced by experience. In fact, silver workers may find overly structured training formats less effective if they perceive them as repetitive or if they lack direct relevance to their everyday work.

Additionally, Ranasinghe (2024, p.2) identified age as a barrier to digital learning, while the results suggest that the limited influence of age and workload on training preferences do not form this barrier. The results highlight that silver workers' engagement is more driven by the relevance of the training content and the perceived benefits of participation. This aligns with previous research showing that silver workers are willing to adapt and upskill, provided the learning environment addresses their needs and motivations effectively (EXPERTISE, 2024, p.30; Cully et al., 2000, p.5).

Finally, the results also provide empirical backing for using Kirkpatrick's four-level training evaluation model (1994) as a framework for assessing training effectiveness among older workers. The model emphasizes not only immediate reactions and new competency acquisition, but also behavioural change and long-term results. While this study did not measure behavioural outcomes directly, the emphasis on practical applicability, perceived relevance, and integration into daily tasks reflects important aspects of the Kirkpatrick's level 3 and 4 outcomes. This alignment suggests that perceived training effectiveness among silver workers may serve as an example for future behavioural change and real-world impact. Learning formats that incorporate real-world tasks or included hands-on practise were generally perceived as more effective, especially when they aligned with the daily responsibilities and constraints of older workers. This suggests that training must move beyond simply delivering content and instead promote behavioural change and practical application in the workplace. To achieve lasting impact, programs should be designed with clear connections to on-the-job tasks and be supported by realistic learning environments and organisational commitment.

### *5.3 Practical implications for upskilling the silver workforce*

The findings of this study offer valuable insights for managers and training designers for developing effective training formats for acquiring Industry 4.0 skills, specifically tailored to silver workers within the context of PSM. Digital methods such as e-learning should not be excluded from training formats. However, they must be carefully integrated into blended strategies that emphasize real-world application, relevance to daily tasks, and opportunities for interaction and feedback. This is in line with insights from the EXPERTISE project (2024, p.17), where they emphasize that training initiatives should be embedded in the day-to-day reality of PSM professionals to maximize engagement and knowledge retention.

Additionally, the findings highlight that training effectiveness depends not only on content delivery, but also on the perceived relevance and how the training is introduced and framed. Silver workers value clear explanations of the benefits, purpose, and applicability of training programs. Silver workers, particularly those near retirement, value clear explanations of the purpose, benefits, and practical relevance of training, as they may be less motivated by long-term career advancement. Managers should actively promote the outcomes of training initiatives and ensure that older employees see how new skills connect to their existing roles and expertise.

Furthermore, organizations that invest in tailored, well-communicated, and practical training formats not only invest in their silver workforce but also strengthen long-term knowledge transfer and innovation. Silver workers bring deep institutional knowledge that can significantly benefit digital transformation efforts if properly supported (Komp-Leukkunen et al., 2022, p. 48). Managers should ensure that learning environments foster both upskilling and intergenerational collaboration, which are two critical elements for sustainable success in Industry 4.0 environments (Delke et al., 2023, p. 13).

Lastly, despite increasing attention to digital transformation in purchasing and supply management, the existing PSM literature offers limited insights into how older professionals engage with training. Much of the current research focuses on the adoption of Industry 4.0 technologies (Delke et al., 2023, p. 1–2) or organizational digital maturity (Rikala et al., 2024, p. 16), while overlooking the specific learning needs and experiences of silver workers. As highlighted by TU Dortmund University (EXPERTISE, 2023, p. 21; 2024, p. 27), most upskilling efforts in PSM are not systematically adapted to this demographic, resulting in a mismatch between training content and learner characteristics.

## 6. LIMITATIONS AND FUTURE RESEARCH: REFINING TRAINING APPROACHES FOR SILVER WORKERS

The findings contribute to a better understanding of effective training methodologies for older professionals in PSM, however, several limitations must be acknowledged. First, the study relies on self-reported survey data which may introduce biases such as social desirability or overestimation of perceived effectiveness. These issues are common with Likert-scales, which, while useful for quantifying subjective perceptions, do not always capture accurate responses (Norman, 2010, p. 625). Second, the data was drawn from the EXPERTISE project and represents only those who voluntarily participated in the survey. As a result, the sample may be subject to self-selection bias, which can affect the generalizability of the results to the broader silver workforce (Osborne, 2008, pp. 39–45). Moreover, the study focussed exclusively on silver workers in PSM roles, limiting the applicability of findings to other sectors or professional contexts.

Third, while the study explored three learning methodologies, it did not account for variations within these categories. For instance, the different types of e-learning or hands-on delivery. These variations in training structure may produce different effectiveness outcomes (Deschacht et al., 2015, p. 85). The analysis also excluded potentially relevant psychological and cognitive variables, such as digital literacy, learning motivation, and openness to change. Froehlich et al. (2022, p.10) and Chillarege (2003, p.380) identify these variables as key to older learners' engagement and success.

A further limitation lies in the study's use of a cross-sectional survey design, which limits the ability to make causal inferences or assess the long-term impact of different training formats. While regression analysis was used to explore predictive relationships, it does not confirm causality, and the findings should be interpreted within that constraint (Bewick et al., 2003, p. 454).

These limitations also highlight several important directions for future research. To build on the current findings, future research should consider examining psychological and motivational factors such as perceived relevance and learning motivation. Prior work by Chillarege (2003, p. 380) and Ranasinghe (2024, p. 2) suggests that such internal factors play a critical role in how older workers approach learning, especially in digital contexts.

In addition, studies focused on long-term goals could offer deeper insights into how different learning methodologies influence long-term behavioural changes and skill application. An emphasis should be placed on Kirkpatrick's level 3 and 4 of the training evaluation model (Kirkpatrick, 1994, pp. 15–16). Future work could also compare variations within learning formats, such as different digital tools, instructional designs, or facilitation, to further pinpoint which specific elements improve learning engagement among silver workers (Deschacht et al., 2015, p. 85).

Broadening the research scope beyond the PSM sector is another key recommendation. Including participants from various industries, countries, and organizational contexts would provide a more comprehensive understanding of how cultural, institutional, and technological factors influence training outcomes (Rikala et al., 2024, p. 16). Incorporating qualitative methods like interviews or focus groups could also complement quantitative findings by capturing the subjective experiences, challenges, and expectations of silver workers. This would offer a richer understanding of how to design inclusive and effective training programs.

Beyond methodological improvements, this study also contributes to the growing body of literature on workforce transformation in purchasing and supply management. As PSM adapts to Industry 4.0 technologies, the ability of organisations to effectively train and integrate older professionals becomes increasingly relevant. The findings highlight how learning preferences and perceived effectiveness vary by individual characteristics, pointing to the need for tailored upskilling strategies that align with both digital competencies and operational realities. By focusing on silver workers in PSM, this research addresses a gap in existing research and highlights the importance of upskilling the silver workforce in the digital era.

## 7. ACKNOWLEDGEMENTS

This research is based on secondary data collected through the EXPERTISE project, which ensured participant anonymity and voluntary participation. As no personally identifiable information was used, privacy and confidentiality were maintained throughout the analysis. Participants provided informed consent, and all data was handled according to ethical standards for survey-based research. The analysis did not involve direct contact with participants or manipulation of any variables. During the production of this work, the author used ChatGPT in order to refine the text. After using this tool/service, the author reviewed and edited the content as needed and takes full responsibility for the content of the work.

Finally, I would like to express my sincere gratitude to my supervisors, Dr. V. Delke and Dr. Ir. N. Pulles, for their thoughtful advice, trust, critical insights, and guidance throughout this research journey. I extend my heartfelt thanks to my boyfriend, family, and friends for their unconditional support throughout my entire studies.

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# Appendix

## *A. Descriptive statistics*

| Age | | Gender | | Experience | | Workload | |
|---|---|---|---|---|---|---|---|
| | | | | | | | |
| Mean | 48,13274336 | Mean | 0,663716814 | Mean | 16,13716814 | Mean | 0,814159292 |
| Standard Error | 1,017817286 | Standard Error | 0,054230946 | Standard Error | 1,019528189 | Standard Error | 0,036754973 |
| Median | 51 | Median | 1 | Median | 15 | Median | 1 |
| Mode | 55 | Mode | 1 | Mode | 25 | Mode | 1 |
| Standard Deviation | 10,81954616 | Standard Deviation | 0,576482862 | Standard Deviation | 10,83773331 | Standard Deviation | 0,390710721 |
| Sample Variance | 117,062579 | Sample Variance | 0,332332491 | Sample Variance | 117,4564633 | Sample Variance | 0,152654867 |
| Kurtosis | -0,173716728 | Kurtosis | 2,77037233 | Kurtosis | -0,065552747 | Kurtosis | 0,692091301 |
| Skewness | -0,690565426 | Skewness | 0,751883085 | Skewness | 0,510787534 | Skewness | -1,63711822 |
| Range | 49 | Range | 3 | Range | 51 | Range | 1 |
| Minimum | 20 | Minimum | 0 | Minimum | 0 | Minimum | 0 |
| Maximum | 69 | Maximum | 3 | Maximum | 51 | Maximum | 1 |
| Sum | 5439 | Sum | 75 | Sum | 1823,5 | Sum | 92 |
| Count | 113 | Count | 113 | Count | 113 | Count | 113 |
| Confidence Level(95,0%) | 2,016674482 | Confidence Level(95,0%) | 0,107451668 | Confidence Level(95,0%) | 2,020064419 | Confidence Level(95,0%) | 0,072825267 |

**Learning Preferences**

| Pref_CustomPaths | | Pref_HandsOn | | Pref_Feedback | | Pref_IndividualPace | | Pref_Materials | |
|---|---|---|---|---|---|---|---|---|---|
| | | | | | | | | | |
| Mean | 7,188976378 | Mean | 8 | Mean | 5,417322835 | Mean | 5,141732283 | Mean | |
| Standard Error | 0,25437855 | Standard Error | 0,174273359 | Standard Error | 0,229779282 | Standard Error | 0,242297777 | Standard Error | |
| Median | 8 | Median | 9 | Median | 5 | Median | 5 | Median | |
| Mode | 10 | Mode | 9 | Mode | 8 | Mode | 5 | Mode | |
| Standard Deviation | 2,866700674 | Standard Deviation | 1,963961012 | Standard Deviation | 2,589480995 | Standard Deviation | 2,73055727 | Standard Deviation | |
| Sample Variance | 8,217972753 | Sample Variance | 3,857142857 | Sample Variance | 6,705411824 | Sample Variance | 7,455943007 | Sample Variance | |
| Kurtosis | -0,705283373 | Kurtosis | 1,126638524 | Kurtosis | -0,951398282 | Kurtosis | -1,049669914 | Kurtosis | |
| Skewness | -0,763922526 | Skewness | -1,232631142 | Skewness | -0,175538376 | Skewness | 0,176720496 | Skewness | |
| Range | 9 | Range | 8 | Range | 9 | Range | 9 | Range | |
| Minimum | 1 | Minimum | 2 | Minimum | 1 | Minimum | 1 | Minimum | |
| Maximum | 10 | Maximum | 10 | Maximum | 10 | Maximum | 10 | Maximum | |
| Sum | 913 | Sum | 1016 | Sum | 688 | Sum | 653 | Sum | |
| Count | 127 | Count | 127 | Count | 127 | Count | 127 | Count | |
| Confidence Level(95,0%) | 0,503407673 | Confidence Level(95,0%) | 0,344881854 | Confidence Level(95,0%) | 0,454726443 | Confidence Level(95,0%) | 0,479500177 | Confidence Level(95,0%) | |

| Pref_IndependentStudy | | Pref_PositiveAttitude | | Pref_DemandOriented | | Pref_InnovativeFormats | | Pref_BenefitsAwareness | |
|---|---|---|---|---|---|---|---|---|---|
| | | | | | | | | | |
| Mean | 5,094488189 | Mean | 5,338582677 | Mean | 4,874015748 | Mean | 4,196850394 | Mean | 3,68503937 |
| Standard Error | 0,224550286 | Standard Error | 0,238789513 | Standard Error | 0,264556737 | Standard Error | 0,249994218 | Standard Error | 0,202379541 |
| Median | 5 | Median | 6 | Median | 4 | Median | 3 | Median | 4 |
| Mode | 3 | Mode | 3 | Mode | 2 | Mode | 2 | Mode | 1 |
| Standard Deviation | 2,530553208 | Standard Deviation | 2,691021145 | Standard Deviation | 2,981403009 | Standard Deviation | 2,81729176 | Standard Deviation | 2,280701603 |
| Sample Variance | 6,403699538 | Sample Variance | 7,241594801 | Sample Variance | 8,888763905 | Sample Variance | 7,937132858 | Sample Variance | 5,2015998 |
| Kurtosis | -0,884845671 | Kurtosis | -1,212813916 | Kurtosis | -1,233776263 | Kurtosis | -1,018959042 | Kurtosis | -0,733947856 |
| Skewness | 0,244406589 | Skewness | 0,089070953 | Skewness | 0,326652089 | Skewness | 0,565940306 | Skewness | 0,404588542 |
| Range | 9 | Range | 9 | Range | 9 | Range | 9 | Range | 8 |
| Minimum | 1 | Minimum | 1 | Minimum | 1 | Minimum | 1 | Minimum | 1 |
| Maximum | 10 | Maximum | 10 | Maximum | 10 | Maximum | 10 | Maximum | 9 |
| Sum | 647 | Sum | 678 | Sum | 619 | Sum | 533 | Sum | 468 |
| Count | 127 | Count | 127 | Count | 127 | Count | 127 | Count | 127 |
| Confidence Level(95,0%) | 0,444378415 | Confidence Level(95,0%) | 0,472557426 | Confidence Level(95,0%) | 0,523550005 | Confidence Level(95,0%) | 0,494731208 | Confidence Level(95,0%) | 0,400503163 |

**Learning Environment Preferences**

| Env_Interactive | | Env_Online | | Env_InPerson | | Env_Blended | | Env_ExchangePlatform | |
|---|---|---|---|---|---|---|---|---|---|
| | | | | | | | | | |
| Mean | 8,346456693 | Mean | 6 | Mean | 6,149606299 | Mean | 6,070866142 | Mean | |
| Standard Error | 0,183488516 | Standard Error | 0,26667604 | Standard Error | 0,253725827 | Standard Error | 0,24395737 | Standard Error | |
| Median | 9 | Median | 7 | Median | 7 | Median | 7 | Median | |
| Mode | 10 | Mode | 9 | Mode | 5 | Mode | 7 | Mode | |
| Standard Deviation | 2,067810562 | Standard Deviation | 3,005286348 | Standard Deviation | 2,859344858 | Standard Deviation | 2,749259936 | Standard Deviation | |
| Sample Variance | 4,27584052 | Sample Variance | 9,031746032 | Sample Variance | 8,175853018 | Sample Variance | 7,558430196 | Sample Variance | |
| Kurtosis | 0,870662506 | Kurtosis | -1,075862597 | Kurtosis | -0,922974709 | Kurtosis | -1,186358616 | Kurtosis | |
| Skewness | -1,296166637 | Skewness | -0,509780092 | Skewness | -0,353816046 | Skewness | -0,196160055 | Skewness | |
| Range | 8 | Range | 9 | Range | 9 | Range | 9 | Range | |
| Minimum | 2 | Minimum | 1 | Minimum | 1 | Minimum | 1 | Minimum | |
| Maximum | 10 | Maximum | 10 | Maximum | 10 | Maximum | 10 | Maximum | |
| Sum | 1060 | Sum | 762 | Sum | 781 | Sum | 771 | Sum | |
| Count | 127 | Count | 127 | Count | 127 | Count | 127 | Count | |
| Confidence Level(95,0%) | 0,363118379 | Confidence Level(95,0%) | 0,527744044 | Confidence Level(95,0%) | 0,502115953 | Confidence Level(95,0%) | 0,482784463 | Confidence Level(95,0%) | |

| Env_SkillHomogeneity | | Env_ConvenientTimes | | Env_CrossGenLearning | | Env_CrossFunctional | | Env_Evaluation | |
|---|---|---|---|---|---|---|---|---|---|
| | | | | | | | | | |
| Mean | 5,173228346 | Mean | 5,417322835 | Mean | 4,417322835 | Mean | 3,708661417 | Mean | 4,165354331 |
| Standard Error | 0,225012182 | Standard Error | 0,218344129 | Standard Error | 0,236480713 | Standard Error | 0,202505934 | Standard Error | 0,236301698 |
| Median | 5 | Median | 5 | Median | 4 | Median | 3 | Median | 4 |
| Mode | 2 | Mode | 5 | Mode | 2 | Mode | 1 | Mode | 1 |
| Standard Deviation | 2,535758514 | Standard Deviation | 2,460613373 | Standard Deviation | 2,665002293 | Standard Deviation | 2,28212598 | Standard Deviation | 2,662984897 |
| Sample Variance | 6,430071241 | Sample Variance | 6,054618173 | Sample Variance | 7,10223722 | Sample Variance | 5,208098988 | Sample Variance | 7,091488564 |
| Kurtosis | -1,028608082 | Kurtosis | -0,948285941 | Kurtosis | -0,639435475 | Kurtosis | -0,939266234 | Kurtosis | -0,944052183 |
| Skewness | 0,235546735 | Skewness | 0,062062009 | Skewness | 0,668598839 | Skewness | 0,528962519 | Skewness | 0,408705616 |
| Range | 9 | Range | 9 | Range | 9 | Range | 7 | Range | 9 |
| Minimum | 1 | Minimum | 1 | Minimum | 1 | Minimum | 1 | Minimum | 1 |
| Maximum | 10 | Maximum | 10 | Maximum | 10 | Maximum | 8 | Maximum | 10 |
| Sum | 657 | Sum | 688 | Sum | 561 | Sum | 471 | Sum | 529 |
| Count | 127 | Count | 127 | Count | 127 | Count | 127 | Count | 127 |
| Confidence Level(95,0%) | 0,445292494 | Confidence Level(95,0%) | 0,432096613 | Confidence Level(95,0%) | 0,467988379 | Confidence Level(95,0%) | 0,400753291 | Confidence Level(95,0%) | 0,467634114 |

**Organisational Training Support**

| *Org_CustomPaths* | | *Org_HandsOn* | | *Org_Feedback* | | *Org_IndividualPace* | | *Org_Materials* | |
|---|---|---|---|---|---|---|---|---|---|
| Mean | 3,224806202 | Mean | 3,573643411 | Mean | 3,565891473 | Mean | 3,465116279 | Mean | |
| Standard Error | 0,09919755 | Standard Error | 0,104278154 | Standard Error | 0,092633834 | Standard Error | 0,101494711 | Standard Error | |
| Median | 3 | Median | 4 | Median | 4 | Median | 4 | Median | |
| Mode | 3 | Mode | 4 | Mode | 3 | Mode | 4 | Mode | |
| Standard Deviation | 1,126667584 | Standard Deviation | 1,184372156 | Standard Deviation | 1,052118111 | Standard Deviation | 1,15275832 | Standard Deviation | |
| Sample Variance | 1,269379845 | Sample Variance | 1,402737403 | Sample Variance | 1,106952519 | Sample Variance | 1,328851744 | Sample Variance | |
| Kurtosis | -0,58080203 | Kurtosis | -0,138961606 | Kurtosis | 0,234554694 | Kurtosis | -0,18159902 | Kurtosis | |
| Skewness | -0,2887834 | Skewness | -0,722900411 | Skewness | -0,605876109 | Skewness | -0,612937298 | Skewness | |
| Range | 4 | Range | 4 | Range | 4 | Range | 4 | Range | |
| Minimum | 1 | Minimum | 1 | Minimum | 1 | Minimum | 1 | Minimum | |
| Maximum | 5 | Maximum | 5 | Maximum | 5 | Maximum | 5 | Maximum | |
| Sum | 416 | Sum | 461 | Sum | 460 | Sum | 447 | Sum | |
| Count | 129 | Count | 129 | Count | 129 | Count | 129 | Count | |
| Confidence Level(95,0%) | 0,1962793 | Confidence Level(95,0%) | 0,206332143 | Confidence Level(95,0%) | 0,183291868 | Confidence Level(95,0%) | 0,200824626 | Confidence Level(95,0%) | |

| *Org_IndependentStudy* | | *Org_PositiveAttitude* | | *Org_DemandOriented* | | *Org_InnovativeFormats* | | *Org_BenefitsAwareness* | |
|---|---|---|---|---|---|---|---|---|---|
| Mean | 3,488372093 | Mean | 3,519379845 | Mean | 3,449612403 | Mean | 3,11627907 | Mean | 3,410852713 |
| Standard Error | 0,097271571 | Standard Error | 0,102713178 | Standard Error | 0,097796236 | Standard Error | 0,099433903 | Standard Error | 0,097579973 |
| Median | 4 | Median | 3 | Median | 3 | Median | 3 | Median | 3 |
| Mode | 4 | Mode | 3 | Mode | 3 | Mode | 3 | Mode | 3 |
| Standard Deviation | 1,104792678 | Standard Deviation | 1,166597451 | Standard Deviation | 1,110751718 | Standard Deviation | 1,129352047 | Standard Deviation | 1,108295447 |
| Sample Variance | 1,22056686 | Sample Variance | 1,360949612 | Sample Variance | 1,23376938 | Sample Variance | 1,275436047 | Sample Variance | 1,228318798 |
| Kurtosis | 0,219866752 | Kurtosis | -0,378597614 | Kurtosis | -0,145684942 | Kurtosis | -0,518156693 | Kurtosis | -0,432904015 |
| Skewness | -0,888166395 | Skewness | -0,422366912 | Skewness | -0,479095568 | Skewness | -0,232226341 | Skewness | -0,348208249 |
| Range | 4 | Range | 4 | Range | 4 | Range | 4 | Range | 4 |
| Minimum | 1 | Minimum | 1 | Minimum | 1 | Minimum | 1 | Minimum | 1 |
| Maximum | 5 | Maximum | 5 | Maximum | 5 | Maximum | 5 | Maximum | 5 |
| Sum | 450 | Sum | 454 | Sum | 445 | Sum | 402 | Sum | 440 |
| Count | 129 | Count | 129 | Count | 129 | Count | 129 | Count | 129 |
| Confidence Level(95,0%) | 0,192468423 | Confidence Level(95,0%) | 0,203235572 | Confidence Level(95,0%) | 0,193506561 | Confidence Level(95,0%) | 0,196746966 | Confidence Level(95,0%) | 0,193078648 |

## *B. Frequency distributions*

| **Learning Preferences** | CustomPa | HandsOn | Feedback | IndividualF | Materials | Independe | PositiveAttitu | DemandOı | Innovative | BenefitsAw |
|---|---|---|---|---|---|---|---|---|---|---|
| *Rated over 6* | 85 | 102 | 49 | 45 | 51 | 40 | 48 | 43 | 33 | 12 |
| *Rated over 8* | 58 | 70 | 11 | 17 | 27 | 13 | 21 | 22 | 13 | 2 |

| **Learning Environment Preferences** | Env_Intera | Env_Online | Env_InPers | Env_Blend | Env_Excha | Env_SkillH | Env_Conveni | Env_Cross | Env_Cross | Env_Evalua |
|---|---|---|---|---|---|---|---|---|---|---|
| *"<=6"* | 25 | 60 | 63 | 62 | 79 | 85 | 85 | 99 | 106 | 98 |
| *">6"* | 102 | 67 | 64 | 65 | 48 | 42 | 42 | 28 | 21 | 29 |
| *">8"* | 74 | 36 | 33 | 32 | 20 | 17 | 20 | 14 | 0 | 8 |

| **Learning Environment Preferences** | Env_Intera | Env_Online | Env_InPers | Env_Blend | Env_Excha | Env_SkillH | Env_Conve | Env_Cross | Env_Cross | Env_Evalua |
|---|---|---|---|---|---|---|---|---|---|---|
| "=1" | 0 | 21 | 14 | 5 | 11 | 4 | 6 | 12 | 25 | 29 |
| "=2" | 2 | 4 | 5 | 12 | 0 | 22 | 12 | 28 | 24 | 18 |
| "=3" | 2 | 8 | 4 | 12 | 26 | 11 | 13 | 17 | 23 | 11 |
| "=4" | 8 | 4 | 11 | 14 | 12 | 20 | 17 | 21 | 8 | 12 |
| "=5" | 1 | 7 | 20 | 10 | 12 | 16 | 19 | 8 | 18 | 16 |
| "=6" | 12 | 16 | 9 | 9 | 18 | 12 | 18 | 13 | 8 | 12 |
| "=7" | 5 | 19 | 17 | 21 | 10 | 15 | 12 | 6 | 9 | 13 |
| "=8" | 23 | 12 | 14 | 12 | 18 | 10 | 10 | 8 | 12 | 8 |
| "=9" | 18 | 27 | 14 | 17 | 14 | 11 | 16 | 6 | 0 | 4 |
| "=10" | 56 | 9 | 19 | 15 | 6 | 6 | 4 | 8 | 0 | 4 |

| **Organisational Training Support** | Org_Custo | Org_Hands | Org_Feedb | Org_Indivic | Org_Mater | Org_Indep | Org_PositiveA | Org_Dema | Org_Innova | Org_Benef |
|---|---|---|---|---|---|---|---|---|---|---|
| *">3"* | 51 | 72 | 66 | 65 | 68 | 73 | 58 | 59 | 45 | 58 |
| *">4"* | 13 | 27 | 22 | 23 | 16 | 16 | 30 | 23 | 11 | 20 |

| **Organisation Training Environment** | Org_Intera | Org_Online | Org_InPers | Org_Blend | Org_Excha | Org_SkillH | Org_Conveni | Org_Cross | Org_Cross | Org_Evalua |
|---|---|---|---|---|---|---|---|---|---|---|
| *">3"* | 51 | 71 | 81 | 56 | 54 | 44 | 56 | 48 | 49 | 61 |
| *">4"* | 11 | 27 | 30 | 25 | 16 | 4 | 17 | 7 | 13 | 22 |

## *C. Pearson's correlation matrix*

| | *Age* | *Gender* | *Experience* | *Workload* | *Pref_HandsOn* | *Env_Online* | *Env_Blended* | *Perceived Effectiveness* |
|---|---|---|---|---|---|---|---|---|
| Age | 1,00 | | | | | | | |
| Gender | -0,07 | 1,00 | | | | | | |
| Experience | 0,18 | -0,05 | 1,00 | | | | | |
| Workload | -0,29 | 0,40 | 0,06 | 1,00 | | | | |
| Pref_HandsOn | 0,01 | 0,10 | 0,11 | 0,09 | 1,00 | | | |
| Env_Online | -0,05 | 0,22 | 0,07 | 0,38 | -0,06 | 1,00 | | |
| Env_Blended | -0,05 | 0,11 | -0,15 | 0,04 | -0,01 | 0,21 | 1,00 | |
| Perceived Effectiveness | -0,04 | 0,08 | 0,38 | 0,08 | 0,02 | 0,09 | 0,00 | 1,00 |

## D. T-tests and one way ANOVA

**H1a** t-Test: Paired Two Sample for Means

| | *Pref_HandsOn* | *Env_Online* |
|---|---|---|
| Mean | 8 | 6 |
| Variance | 3,857142857 | 9,03174603 |
| Observations | 127 | 127 |
| Pearson Correlation | -0,056475492 | |
| Hypothesized Mean Difference | 0 | |
| df | 126 | |
| t Stat | 6,121716249 | |
| P(T<=t) one-tail | 5,43008E-09 | |
| t Critical one-tail | 1,657036982 | |
| P(T<=t) two-tail | 1,08602E-08 | |
| t Critical two-tail | 1,978970602 | |

**H1b** t-Test: Paired Two Sample for Means

| | *Env_Blended* | *Pref_HandsOn* |
|---|---|---|
| Mean | 6,070866142 | 8 |
| Variance | 7,558430196 | 3,85714286 |
| Observations | 127 | 127 |
| Pearson Correlation | -0,014698763 | |
| Hypothesized Mean Difference | 0 | |
| df | 126 | |
| t Stat | -6,390234509 | |
| P(T<=t) one-tail | 1,46156E-09 | |
| t Critical one-tail | 1,657036982 | |
| P(T<=t) two-tail | 2,92311E-09 | |
| t Critical two-tail | 1,978970602 | |

**H1c** t-Test: Paired Two Sample for Means

| | *Env_Blended* | *Env_Online* |
|---|---|---|
| Mean | 6,070866142 | 6 |
| Variance | 7,558430196 | 9,031746032 |
| Observations | 127 | 127 |
| Pearson Correlation | 0,209403669 | |
| Hypothesized Mean Difference | 0 | |
| df | 126 | |
| t Stat | 0,220399508 | |
| P(T<=t) one-tail | 0,412958372 | |
| t Critical one-tail | 1,657036982 | |
| P(T<=t) two-tail | 0,825916743 | |
| t Critical two-tail | 1,978970602 | |

**H2** Anova: Single Factor

SUMMARY

| *Groups* | *Count* | *Sum* | *Average* | *Variance* |
|---|---|---|---|---|
| Pref_HandsOn | 127 | 1016 | 8 | 3,85714 |
| Env_Online | 127 | 762 | 6 | 9,03175 |
| Env_Blended | 127 | 771 | 6,07087 | 7,55843 |

ANOVA

| *Source of Variation* | *SS* | *df* | *MS* | *F* | *P-value* | *F crit* |
|---|---|---|---|---|---|---|
| Between Groups | 327,0918635 | 2 | 163,546 | 23,9952 | 1,54661E-10 | 3,019600042 |
| Within Groups | 2576,362205 | 378 | 6,81577 | | | |
| | | | | | | |
| Total | 2903,454068 | 380 | | | | |