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STARA Awareness, Learning Goal Orientation, and Knowledge Sharing Behavior among Tech Professionals in Jakarta

Lutfita Astifani Rundana[1*], Achmad Fajar Hendarman[2]
[1]Institut Teknologi Bandung, Bandung, Indonesia, 29324329@mahasiswa.itb.ac.id.
[2]Institut Teknologi Bandung, Bandung, Indonesia, achmad.fajar@sbm-itb.ac.id.

*Corresponding Author, 29324329@mahasiswa.itb.ac.id[1]

Abstract: The rapid adoption of Smart Technology, Artificial Intelligence, Robotics, and Algorithms (STARA) is transforming technology-related occupations and increasing employees' concerns regarding job security and continuity. These concerns may influence employees' willingness to participate in knowledge-sharing activities, particularly when technological developments are perceived as potential threats. This study examines the effects of STARA Awareness on Knowledge Collecting and Knowledge Donating while assessing the moderating role of Learning Goal Orientation (LGO) among technology professionals in Jakarta. Data were collected from 124 respondents using a quantitative survey approach and analyzed through Partial Least Squares Structural Equation Modeling (PLS-SEM). The results indicate that STARA Awareness has significant negative effects on Knowledge Collecting ($\beta = -0.206$) and Knowledge Donating ($\beta = -0.169$). In contrast, LGO demonstrates positive effects on Knowledge Collecting ($\beta = 0.490$) and Knowledge Donating ($\beta = 0.431$). Furthermore, LGO significantly moderates the negative relationships between STARA Awareness and both dimensions of knowledge-sharing behavior. These findings suggest that Learning Goal Orientation functions as an important psychological resource that enables technology professionals to maintain knowledge exchange despite ongoing technological disruption.

Keywords: STARA Awareness, Learning Goal Orientation, Knowledge Collecting, Knowledge Donating, Technology Professionals.

INTRODUCTION

Contemporary work increasingly emphasizes knowledge, expertise, professional judgment, and specialized competencies rather than relying solely on physical effort and standardized routines (Drucker, 1967; Taylor, 1911). Since a substantial portion of organizational knowledge is embedded in individual employees, employee mobility may lead to the loss of valuable expertise. Knowledge sharing therefore plays a critical role in transforming individual know-how into organizational capabilities and fostering innovation (Hair & Alamer, 2022; Yildiz et al., 2024). Within this process, knowledge donating refers to the voluntary transfer of knowledge to colleagues, whereas knowledge collecting involves seeking and acquiring knowledge from coworkers (Jnaneswar & Ranjit, 2020a). Both activities depend on employees' willingness to engage in knowledge exchange and cannot be fully explained by the availability of formal organizational mechanisms alone.

Nevertheless, knowledge exchange may be hindered when employees perceive their expertise as a personal resource that contributes to their professional value or employment security. Previous studies have identified organizational justice, interpersonal relationships, organizational culture, and situational conditions as important factors influencing knowledge-sharing behavior (Jnaneswar & Ranjit, 2020a; Karagoz et al., 2020a; Mueller, 2015; Riege, 2005). Employees may become increasingly reluctant to share their knowledge when they perceive that doing so could threaten their position or reduce the uniqueness and value of their expertise (Li et al., 2025). This concern has become increasingly relevant as technological transformation reshapes occupational demands and creates greater uncertainty regarding the future of technology-related jobs.

One significant form of technological transformation is represented by Smart Technology, Artificial Intelligence, Robotics, and Algorithms (STARA). STARA Awareness refers to employees' perceptions that these technologies may affect, transform, or potentially replace certain aspects of their jobs, organizations, or industries (Brougham & Haar, 2018a). Previous research has associated STARA Awareness with a range of occupational and psychological outcomes, including organizational commitment, career satisfaction, turnover intention, cynicism, and depression (Brougham & Haar, 2018a). However, employees do not respond uniformly to technological transformation. While some may perceive technological developments as opportunities for growth and professional development, others may interpret them as threats to valued resources, professional identity, and future employment security (Ma et al., 2021; Tan et al., 2023a).

This issue is especially pertinent to technology professionals because advances in artificial intelligence are altering tasks, skill requirements, and patterns of knowledge use. Recent evidence suggests that exposure to AI can influence work processes and knowledge-related activities (C.-R. Li et al., 2026, Yee et al., 2025). Technology workers therefore face a dual demand, they must continually refresh their competencies while remaining uncertain about the future relevance of existing expertise. In Indonesia, this challenge is compounded by growing demand for highly educated workers and organizational difficulties in retaining skilled talent (Das et al., 2019). Employee mobility may consequently create knowledge loss that extends beyond the departure of an individual worker (Yıldız et al., 2024).

Compensation-based responses may not be sufficient to address this problem. Inflation, exchange-rate movements, and financing pressures can restrict an organization's capacity to repeatedly adjust financial rewards (Ibrahimov et al., 2025, Mitra et al., 2023). Organizations therefore also need behavioral and psychological resources that support cooperation when employees face uncertainty created by technological change. Individual variation in the way employees interpret technological disruption is consequently an important consideration.

Learning Goal Orientation (LGO) provides an important individual-level perspective for understanding employees' responses to challenging work situations. LGO refers to an individual's tendency to develop competence, acquire new skills, and improve mastery when facing complex or demanding tasks (VandeWalle, 1997a). Employees characterized by a strong learning orientation are more likely to perceive difficulties as opportunities for personal development and knowledge acquisition rather than solely as potential threats. Previous research suggests that goal orientation influences how employees appraise and respond to workplace stressors (Ma et al., 2021). In addition, LGO has been shown to contribute to knowledge-sharing behavior within collaborative research environments, indicating its potential role in encouraging employees to exchange knowledge and expertise (Lei, 2024b).

Recent AI research provides additional support for considering LGO in technology-related uncertainty. He et al. (2026) show that learning orientation can shape employees' responses to AI use, while Wang & Wang (2022) emphasize the psychological consequences associated with AI-related anxiety. These studies, however, address AI utilization and AI anxiety rather than the perceived employment threat captured by STARA Awareness. Similarly, STARA studies have concentrated largely on psychological and career-related consequences. Brougham & Haar (2018a), for instance, connected STARA Awareness with commitment, career satisfaction, turnover intention, cynicism, and depression, whereas Tan et al. (2023b) examined employees' challenge and hindrance appraisals of STARA. Whether STARA Awareness changes employees' willingness to collect and donate knowledge remains insufficiently examined.

The knowledge-sharing literature also leaves room for further investigation in this context. Jnaneswar & Ranjit (2020) considered knowledge sharing in relation to organizational justice and innovative behavior, Karagoz et al. (2020) examined contextual conditions that facilitate or impede knowledge exchange in ICT projects and Lei (2024) investigated goal orientation and knowledge-sharing behavior among higher-education research teams. Although these studies establish the relevance of knowledge sharing and learning orientation, they do not directly address situations in which employees perceive technological disruption as a possible threat to their employment. He et al. (2026) likewise focused on the relationship between LGO, AI use, and status conferral rather than its potential buffering effect on knowledge sharing under technological threat.

The literature therefore leaves an unresolved question about how a learning-oriented disposition shapes knowledge exchange when employees face technological disruption. In particular, empirical evidence is limited regarding whether LGO changes the relationship between STARA Awareness and the two forms of knowledge sharing Knowledge Collecting and Knowledge Donating among technology professionals in Jakarta, Indonesia. Addressing this issue requires an integrated framework that considers perceived technological threats, individual learning orientations, and employees' willingness to engage in collaborative knowledge exchange. From a conceptual perspective, heightened STARA Awareness may lead employees to protect their personal knowledge resources and become less willing to disclose or share their expertise. In contrast, employees with a stronger Learning Goal Orientation are more likely to perceive technological changes as opportunities to develop their competencies, seek feedback, collaborate with others, and exchange knowledge (Lei, 2024b; C. Li et al., 2025; VandeWalle, 1997a).

Building on this perspective, the present study examines the effect of STARA Awareness on two dimensions of knowledge-sharing behavior, namely Knowledge Collecting and Knowledge Donating. The study also investigates the contribution of Learning Goal Orientation to both forms of knowledge exchange and assesses whether LGO moderates the relationships between STARA Awareness and each knowledge-sharing outcome among technology professionals in Jakarta. This research extends previous studies by connecting employees' perceptions of technological replacement with organizational knowledge-sharing behavior and by positioning Learning Goal Orientation as a potential psychological resource that may mitigate negative behavioral responses to technological disruption.

METHODS

Research Design

This study adopted a quantitative research approach to examine the relationships among STARA Awareness, Knowledge Sharing Behavior, and Learning Goal Orientation (LGO) among technology professionals in Jakarta. The research was conducted through a systematic and iterative sequence of stages, starting with the identification of the practical issue and progressing through problem definition, literature examination, conceptual framework development, research instrument preparation, data processing, statistical analysis, interpretation of findings, and formulation of recommendations. The selected constructs were reviewed in terms of their novelty, relevance, and alignment with the defined research scope before being finalized.

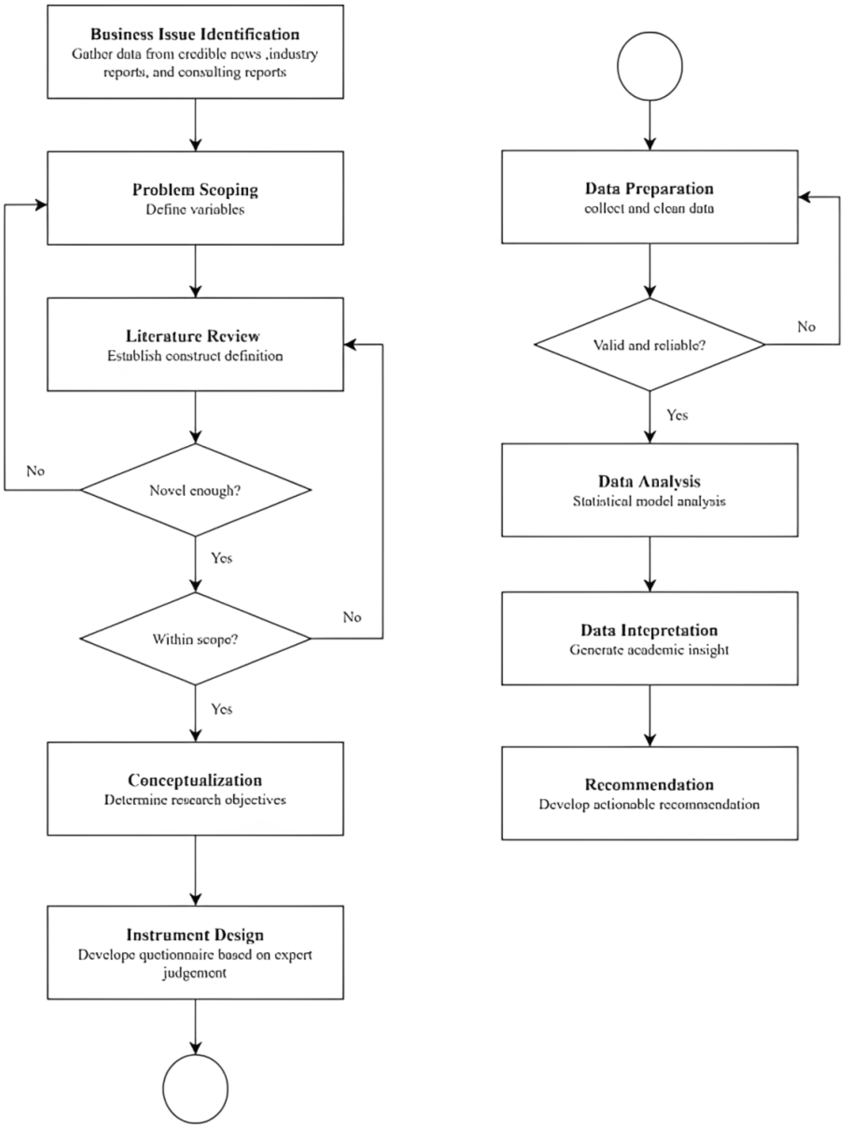

Figure 1. Research Design

Figure 1 illustrates the overall sequence of the research process. The study began by identifying the practical problem and collecting relevant supporting information from reliable news sources, industry and consulting reports, as well as government publications. The identified issue was Therefore refined to determine the key variables relevant to the research. A review of the existing literature was then conducted to establish the theoretical and empirical foundation of the proposed constructs. Several assessments of the study's novelty and scope were undertaken to ensure that the selected variables were appropriate before the research framework was finalized. The resulting framework focused on STARA Awareness, Knowledge Sharing Behavior, and Learning Goal Orientation among technology professionals in Jakarta.

Upon confirming the constructs, a conceptual model was constructed to detail the research objectives and hypothesized variable interactions. Measurement items and survey questionnaires were then developed and subjected to expert review. This crucial step ensured the instrument's validity before primary data collection began.

The concluding stages involved data preparation, validation, analysis, and the formulation of actionable recommendations. To evaluate the model and test the hypotheses, Partial Least Squares Structural Equation Modeling (PLS-SEM) was employed using SmartPLS 3. This analytical approach was chosen because the model incorporates a moderating variable, the target respondents are localized within a specific geographic area, and the acquired sample size was highly suitable for the intended analysis.

Data Collection Method

Primary data was collected using an online survey administered via Google Forms, targeting technology professionals who met the study's specific inclusion criteria. To ensure privacy, participation was strictly voluntary, and no personally identifiable information was collected. The target population consisted of active employees working in technology-centric roles within Jakarta-based organizations.

To maintain analytical consistency, eligible respondents were categorized into six core professional domains based on their primary functional responsibilities. These categories include, Cloud, Infrastructure and DevOps, Data and Analytics, Design and User Experience, Product and Business Analysis, Software Engineering and Development, and Quality and Testing.

Table 1. Field of Expertise Categorization

Fields of Expertise	Explanation	Job Role Example
Cloud, Infrastructure & DevOps	The professional domain tasked with the deployment, administration, and continuous upkeep of the foundational technology infrastructure required to operate systems and applications.	DevOps Engineer, Platform Engineer, Cloud Platform Engineer
Data & Analytics	A field focused on the collection, processing, and analysis of data for company needs.	Data Analyst, Data Scientist, Machine Learning Engineer
Design & User Experience	A field focused on designing the user interface and user experience of a digital product.	UI/UX Designer
Product & Business Analysis	A field that acts as a bridge between business needs and the technical solutions to be developed.	Product Manager, Project Manager, System Analyst
Software Engineering & Development	A field responsible for the design and development of software.	Software Engineer, Software Developer
Quality & Testing	A field responsible for ensuring that software products function according to specifications before being used by end users.	QA Engineer

During the data screening phase, this six-domain classification framework was utilized to verify respondent eligibility and systematically categorize their professional backgrounds. Following this screening process, a total of 124 valid observations were retained for the final statistical analysis.

Sample Size Determination

To ensure the sample size was adequate for hypothesis testing, an a priori power analysis was executed using G*Power 3. The parameters, an F-test for fixed-model multiple regression, an effect size (f^2) of 0.15, an α level of 0.05, a statistical power of 0.95, and three predictors, yielded a minimum requirement of 119 observations. As illustrated in Figure 2, the final collection of 124 valid responses surpassed this baseline, confirming the sample's suitability for PLS-SEM analysis (Faul et al., 2007, 2009).

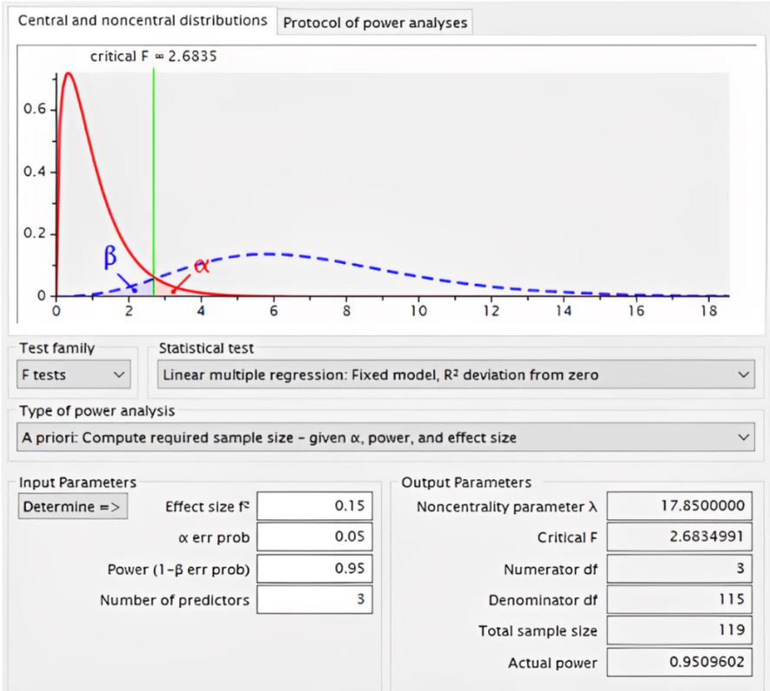

Figure 2. G*Power Result

The G*Power output therefore established 119 observations as the minimum target for the study. Because 124 valid responses were ultimately obtained, the achieved sample surpassed the required benchmark and was retained for the empirical analysis.

Measurement of Variables

The study assessed three primary constructs, STARA Awareness, Knowledge Sharing Behavior, and Learning Goal Orientation (LGO), using previously validated Likert-scale indicators. STARA Awareness was operationalized via four items adapted from Brougham & Haar (2018b), focusing on employees' anxieties regarding technology replacing their roles, organizations, or industries. Knowledge Sharing Behavior, drawing from Jnaneswar & Ranjit (2020b) and Lin (2007) was divided into Knowledge Donating (proactively communicating insights and treating knowledge exchange as a norm) and Knowledge Collecting (actively seeking information and answering peer requests). Learning Goal Orientation (LGO) was adapted from Lei (2024a) and VandeWalle (1997b) to capture an individual's drive to enhance competence, seek out new skills, and embrace challenging tasks. The full set of measurement items is provided in the research appendices, Appendix A for STARA Awareness, Appendix B for Knowledge Sharing Behavior, and Appendix C for Learning Goal Orientation.

Data Analysis Method

The collected survey data were evaluated using Partial Least Squares Structural Equation Modeling (PLS-SEM) via the SmartPLS 3 software. This analytical approach was chosen specifically for its robust capacity to compute interaction effects, thereby enabling the assessment of predictor-outcome relationships across varying levels of a moderating variable. Furthermore, the application of PLS-SEM aligns optimally with the study's empirical constraints and characteristics, such as the acquired sample size, the localized geographic focus, and the highly specific professional nature of the target respondents (Guenther et al., 2023, J. Hair & Alamer, 2022, J. F. Hair et al., 2019).

Prior to hypothesis testing, the initial dataset underwent a rigorous screening process to ensure data completeness and overall suitability. Given that all variables were derived from a single survey instrument, the potential for Common Method Bias was assessed employing a full-collinearity approach based on the Variance Inflation Factor (VIF) values among the latent variables (Kock, 2015). Therefore, descriptive statistics were generated to profile the respondents, providing a foundational context for the interpretation of the inferential findings.

Prior to assessing the structural relationships, the measurement model was thoroughly evaluated. Convergent validity was determined using indicator loadings and the Average Variance Extracted (AVE). While loadings of 0.708 or higher were deemed satisfactory, items falling between 0.40 and 0.70 were retained provided that the broader validity and reliability metrics remained robust. An AVE threshold of 0.50 or greater was utilized to confirm acceptable convergent validity. To gauge internal consistency, Cronbach's alpha, Composite Reliability, and Dijkstra-Henseler's rho (ρA) were analyzed. Metrics meeting or exceeding 0.70 were considered acceptable, though scores surpassing 0.95 were flagged as potential evidence of indicator redundancy (J. Hair & Alamer, 2022, J. F. Hair et al., 2019)

To establish discriminant validity, the study evaluated cross-loadings, the Fornell-Larcker criterion, and the Heterotrait-Monotrait (HTMT) ratio. The HTMT ratio was specifically incorporated as a more robust and sensitive measure of construct distinctiveness. For this metric, values falling below 0.85 were considered indicative of optimal discriminant validity, although a more relaxed threshold of 0.90 was deemed acceptable under certain contextual conditions (Henseler et al., 2015).

Following the successful validation of the measurement model, the structural model was evaluated to determine collinearity, path coefficients, and hypothesis significance. To detect potential multicollinearity, inner Variance Inflation Factor (VIF) scores were scrutinized, with values approximating or falling below 3 deemed optimal. Therefore, a bootstrapping procedure was applied to generate sampling distributions for the path coefficients, allowing for the calculation of t-statistics and p-values. Hypothesized relationships were accepted as statistically significant at the 5% alpha level ($p < 0.05$), provided their corresponding t-statistics surpassed the established critical thresholds (Guenther et al., 2023, J. Hair & Alamer, 2022, J. F. Hair et al., 2019).

The explanatory power of the model was assessed using the coefficient of determination (R^2), whereas the f^2 metric was utilized to measure the incremental contribution of each individual predictor. Following standard guidelines, R^2 values were classified as indicating substantial (0.75), moderate (0.50), or weak (0.25) explanatory power. Similarly, f^2 effect sizes were categorized as small, medium, and large based on the respective thresholds of 0.02, 0.15, and 0.35 (Cohen, 1988, J. F. Hair et al., 2019).

Supplementary analyses were performed to further elucidate both the direct relationships and the moderation effects. The direct paths were evaluated independently of the moderating variable, whereas the moderation effect itself was assessed by testing the interaction between STARA Awareness and LGO. Finally, a simple-slope analysis was employed to visually demonstrate how the relationship between STARA Awareness and the specific dimensions of knowledge sharing fluctuates across low and high levels of LGO (Becker et al., 2023, Guenther et al., 2023).

RESULTS AND DISCUSSION

Respondent Characteristics

A final sample of 124 valid responses was utilized for the statistical analysis. To establish a comprehensive profile of the respondents and contextualize the subsequent model findings, the sample data was categorized according to generational cohort, professional specialization, and the frequency of artificial intelligence (AI) utilization.

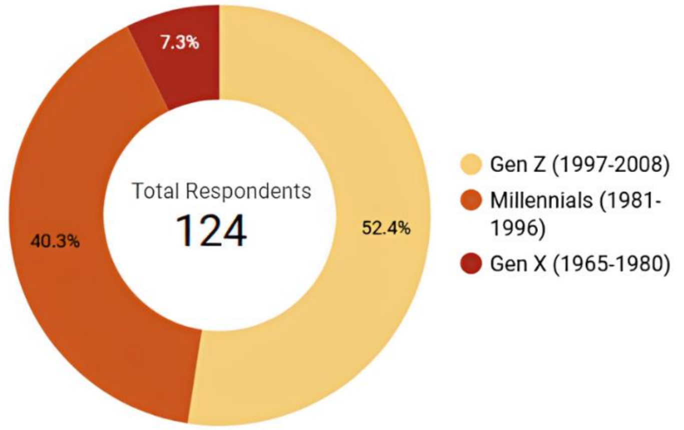

Figure 3. Total Respondents per Generation

The demographic profile of the sample was predominantly composed of Generation Z professionals (born between 1997 and 2008), representing the largest segment with 65 respondents. Millennials (born between 1981 and 1996) constituted the second-largest group with 50 participants, followed by 9 respondents from Generation X (born between 1965 and 1980). Consequently, the participant distribution was heavily concentrated within the Generation Z and Millennial cohorts.

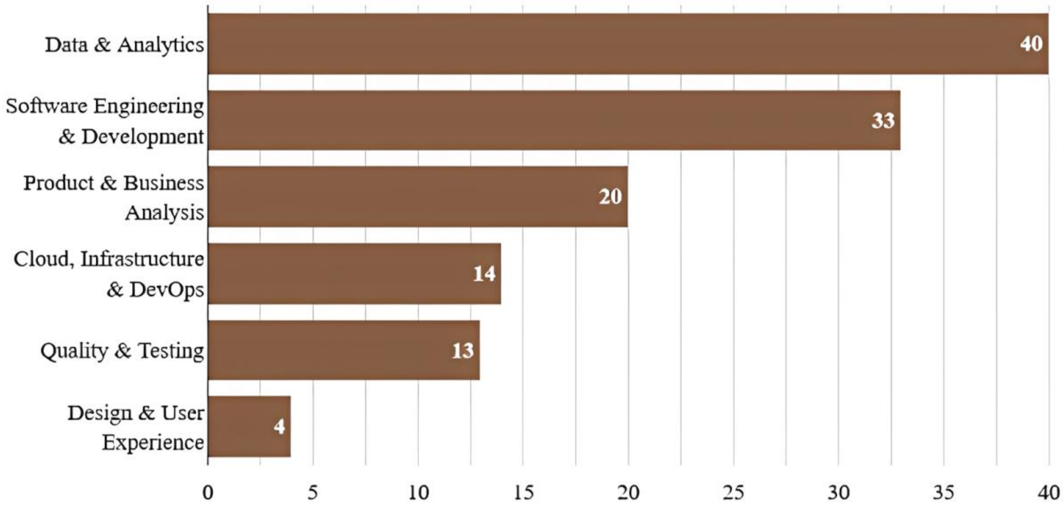

Figure 4. Total Respondents per Field of Expertise

All respondents were first evaluated based on the study's criteria for technology professionals and were Therefore classified into one of six expertise domains: Cloud, Infrastructure and DevOps, Data and Analytics, Design and User Experience, Product and Business Analysis, Software Engineering and Development, and Quality and Testing. This classification was applied in accordance with the domain structure established in the research methodology.

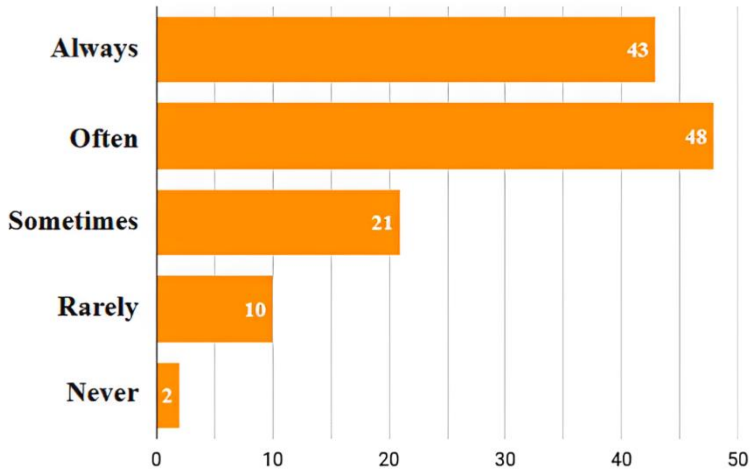

Figure 5. Total Respondents per AI Usage Frequency

AI-use frequency was additionally measured to provide a clearer picture of respondents' exposure to artificial intelligence within their professional activities. The resulting descriptive classifications offer further context regarding the technological environment represented by the sample.

Overall, the descriptive characteristics indicate that the respondents fulfilled the established inclusion criteria while displaying variation in terms of age group, area of technological expertise, and level of exposure to AI. These characteristics provide an important contextual foundation for interpreting the subsequent PLS-SEM analysis.

Measurement Model Assessment

Before examining the structural relationships, the measurement model was first evaluated to ensure that the observed indicators achieved sufficient reliability, convergent validity, and discriminant validity in representing their respective latent constructs.

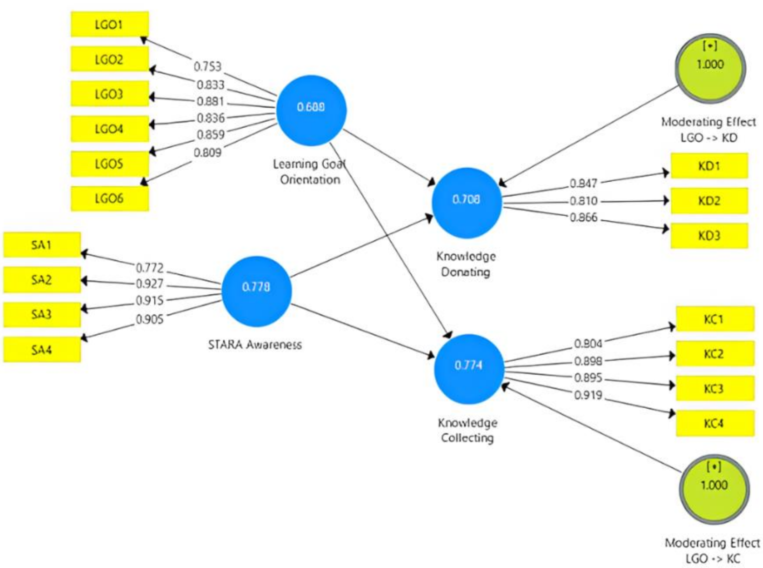

Figure 6. Measurement Model Assessment Results

The measurement assessment indicated that all indicators achieved outer loading values exceeding 0.708, demonstrating satisfactory indicator reliability. Consequently, none of the measurement items needed to be removed. Furthermore, all constructs obtained Average Variance Extracted (AVE) values greater than 0.50, confirming that each latent construct accounted for more than half of the variance in its respective indicators and therefore satisfied the criteria for convergent validity.

Internal consistency reliability was further confirmed through Dijkstra-Henseler's rho (ρA). The resulting coefficients ranged from 0.815 to 0.914, comprising 0.911 for STARA Awareness, 0.913 for Learning Goal Orientation, 0.914 for Knowledge Collecting, and 0.815 for Knowledge Donating. All coefficients remained within the recommended range of 0.70 to 0.95, indicating satisfactory reliability without evidence of excessive redundancy among the measurement indicators.

Table 2. Construct Reliability & Validity Result

Variables	Threshold	ρA
STARA Awareness	$0.70 < x < 0.95$	0.911
Learning Goal Orientation	$0.70 < x < 0.95$	0.913
Knowledge Collecting	$0.70 < x < 0.95$	0.914
Knowledge Donating	$0.70 < x < 0.95$	0.815

The HTMT findings further confirm that discriminant validity was adequately established among the constructs. The highest HTMT value was 0.745 between Knowledge Collecting and Knowledge Donating, which remained below the recommended threshold of 0.85. The other HTMT ratios were 0.652 for the relationship between Knowledge Collecting and Learning Goal Orientation, 0.622 for Knowledge Donating and Learning Goal Orientation, 0.280 for Knowledge Collecting and STARA Awareness, 0.235 for Knowledge Donating and STARA Awareness, and 0.087 for Learning Goal Orientation and STARA Awareness. Overall, these results demonstrate that the constructs exhibit sufficient empirical distinctiveness from one another, supporting discriminant validity (Henseler et al., 2015).

Table 3. Heterotrait-Monotrait Ratio (HTMT) Result

Construct	Knowledge Collecting	Knowledge Donating	Learning Goal Orientation
Knowledge Donating	0.745	-	-
Learning Goal Orientation	0.652	0.622	-
STARA Awareness	0.280	0.235	0.087

Overall, the measurement indicators demonstrated satisfactory convergent validity, internal consistency reliability, and discriminant validity. These results indicate that the latent constructs were measured adequately and could therefore be retained for the subsequent assessment of the structural model and hypothesized relationships.

Structural Model Assessment

The structural model was evaluated in several stages, starting with an assessment of collinearity, followed by hypothesis testing and an examination of the model's explanatory power. The inner VIF values were all below the recommended threshold of 3.0, with a value of 1.096 for Learning Goal Orientation and 1.005 for STARA Awareness in both the Knowledge Collecting and Knowledge Donating models. These findings indicate that multicollinearity was not a significant issue, suggesting that the estimated structural paths could be interpreted with confidence.

Table 4. Inner VIF Result

Predictor	Knowledge Collecting	Knowledge Donating
Learning Goal Orientation	1.096	1.096
STARA Awareness	1.005	1.005

The inner VIF findings indicate that the predictor constructs were free from problematic multicollinearity. All VIF values remained below the recommended threshold, suggesting that the structural path estimates were not substantially affected by excessive overlap among the predictor variables.

Hypothesis testing was conducted using a bootstrapping procedure based on the original path coefficients, t-statistics, and p-values. A 5% significance level was applied, with relationships considered significant when the t-statistic exceeded 1.64 and the p-value was below 0.05. The results showed that STARA Awareness had negative relationships with both Knowledge Collecting and Knowledge Donating, indicating that stronger perceptions of potential technological displacement were associated with lower levels of knowledge-sharing behavior. However, the magnitude of these relationships was relatively small, suggesting that statistical significance should not be interpreted as evidence of a substantial practical effect.

In contrast, Learning Goal Orientation (LGO) demonstrated positive and statistically significant effects on both dimensions of knowledge sharing. The path coefficient for Knowledge Collecting was 0.490 ($t = 8.125$, $p < 0.001$), while the coefficient for Knowledge Donating was 0.431 ($t = 6.353$, $p < 0.001$). These findings indicate that employees with stronger learning-oriented tendencies were more actively involved in both obtaining knowledge from colleagues and sharing their own knowledge with others.

The moderation analysis also produced significant interaction effects for both knowledge-sharing outcomes. For Knowledge Collecting, the interaction coefficient between STARA Awareness and LGO was 0.261 ($t = 4.162$, $p < 0.001$), whereas the corresponding coefficient for Knowledge Donating was 0.269 ($t = 4.126$, $p < 0.001$). The positive interaction coefficients indicate that higher levels of LGO weakened the negative effects of STARA Awareness on both forms of knowledge-sharing behavior. Thus, employees with stronger learning orientations appeared better able to maintain knowledge exchange despite perceiving greater technological disruption.

Table 5. Moderation Analysis

Moderating Effect	Original Sample	t-statistic	p-value
LGO → Knowledge Collecting	0.261	4.162	0.000
LGO → Knowledge Donating	0.269	4.126	0.000

The model's explanatory power was further assessed using f^2 effect size estimates. Learning Goal Orientation (LGO) showed the strongest contribution to both dimensions of knowledge-sharing behavior, with f^2 values of 0.450 for Knowledge Collecting and 0.303 for Knowledge Donating. By comparison, STARA Awareness produced smaller effect sizes of 0.087 for Knowledge Collecting and 0.051 for Knowledge Donating. The moderating effects of LGO also demonstrated meaningful contributions, with f^2 values of 0.218 for Knowledge Collecting and 0.202 for Knowledge Donating. Overall, these results indicate that LGO plays a considerably stronger role in explaining variations in knowledge-sharing behavior than the direct effects of STARA Awareness.

Advanced Analysis

The advanced analysis was conducted to provide a more comprehensive interpretation of the direct and interaction effects estimated by the structural model. The interpretation considered the path coefficients, significance levels, and effect sizes simultaneously to assess both the direction and practical magnitude of the relationships.

STARA Awareness exhibited negative and statistically significant relationships with both dimensions of knowledge-sharing behavior. Its effect on Knowledge Collecting was represented by a path coefficient of -0.206 ($t = 3.319$, $p = 0.001$), providing support for H1a. Similarly, STARA Awareness had a negative effect on Knowledge Donating, with a path coefficient of -0.169 ($t = 2.676$, $p = 0.007$), supporting H1b. These findings suggest that employees who perceive a greater likelihood of technological substitution tend to participate less actively in knowledge exchange. However, the corresponding effect-size values indicate that the magnitude of these direct effects remains relatively limited, suggesting that STARA Awareness has a statistically significant but comparatively weak practical influence on knowledge-sharing behavior.

The results for LGO showed an opposing pattern. Its path coefficient for Knowledge Collecting was 0.490 ($t = 8.125$, $p < 0.001$), while the coefficient for Knowledge Donating was 0.431 ($t = 6.353$, $p < 0.001$). The reported f^2 values indicate that LGO had a large effect on Knowledge Collecting and a medium effect on Knowledge Donating. This finding suggests that employees with stronger learning-oriented tendencies were more actively engaged in seeking knowledge from colleagues and were also more inclined to contribute their own knowledge to others.

The interaction effects further demonstrate that LGO influences the strength of the relationships involving STARA Awareness. The moderation coefficient was 0.261 for Knowledge Collecting ($t = 4.162$, $p < 0.001$) and 0.269 for Knowledge Donating ($t = 4.126$, $p < 0.001$). The positive coefficients indicate that the negative relationship between STARA Awareness and knowledge-sharing behavior becomes weaker as employees' levels of LGO increase. In other words, a stronger learning orientation appears to buffer the adverse influence of perceived technological disruption on both knowledge-seeking and knowledge-sharing behavior.

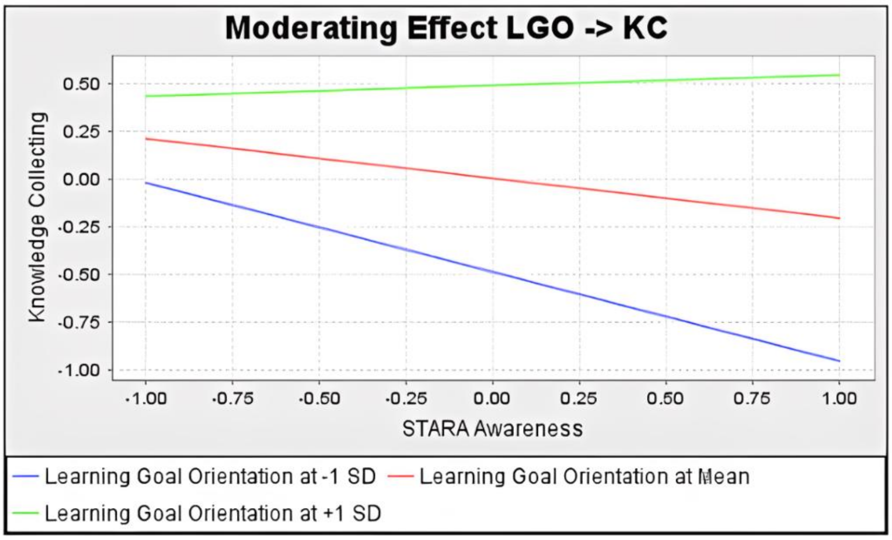

Figure 7. Moderating Effect of Learning Goal Orientation and Knowledge Collecting

The simple-slope analysis presented in Figure 7 provides further insight into the moderating role of LGO. When LGO was low (-1 SD), the relationship between STARA Awareness and Knowledge Collecting followed a negative slope, indicating that stronger perceptions of technological replacement were associated with reduced knowledge-collection behavior. In contrast, at high levels of LGO (+1 SD), the slope became positive. This pattern suggests that employees with a strong learning orientation are more capable of maintaining, and potentially increasing, their efforts to obtain knowledge even when they experience greater concerns about technological displacement.

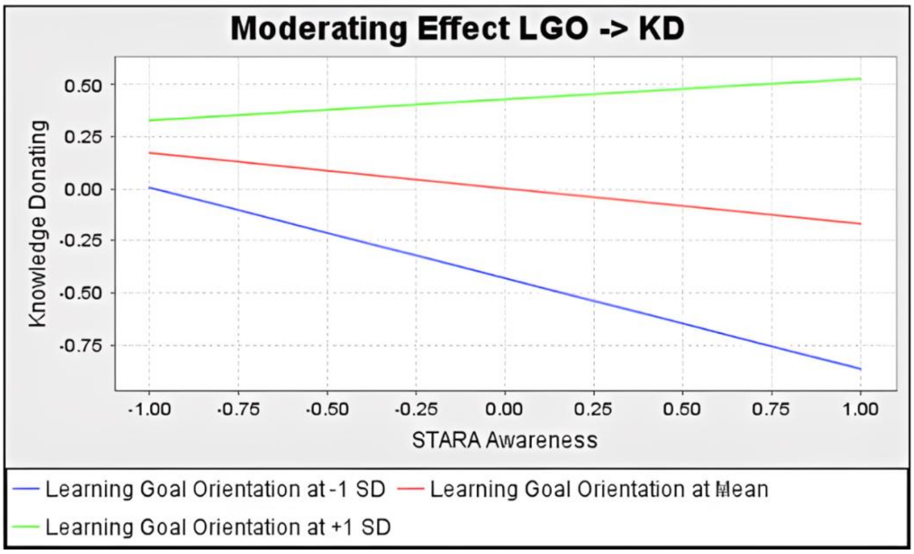

Figure 8. Moderating Effect of Learning Goal Orientation and Knowledge Donating

Knowledge Donating demonstrated a similar interaction pattern. At a low level of LGO (-1 SD), higher STARA Awareness was associated with a noticeable reduction in knowledge-donating behavior. However, when LGO was high (+1 SD), the relationship shifted to a positive direction, indicating that a stronger learning orientation may enable employees to maintain or even enhance their willingness to share knowledge despite experiencing greater perceptions of technological threats.

Overall, the simple-slope findings reinforce the role of LGO as a buffering psychological resource. Technology professionals with strong learning-oriented tendencies appear more capable of sustaining knowledge exchange when STARA Awareness is high, whereas employees with weaker levels of LGO tend to experience a more substantial decline in knowledge-sharing behavior as perceptions of technological disruption increase.

Discussion

The findings show that STARA Awareness is significantly associated with lower levels of both Knowledge Collecting and Knowledge Donating. In practical terms, employees who perceive a greater possibility that Smart Technology, Artificial Intelligence, Robotics, and Algorithms may replace aspects of their jobs tend to engage less actively in knowledge exchange. Nevertheless, the relatively small effect sizes suggest that STARA Awareness represents only one of several factors shaping employees' decisions to acquire or share expertise.

In contrast, Learning Goal Orientation (LGO) demonstrates a positive relationship with both dimensions of knowledge-sharing behavior. Employees who prioritize continuous learning, competence development, and challenging work are more likely to participate in Knowledge Collecting and Knowledge Donating. The comparatively stronger relationship with Knowledge Collecting indicates that a learning-oriented mindset may be particularly important in motivating employees to actively seek information, skills, and expertise from their colleagues as part of their ongoing professional development.

The moderation results provide further insight into the differences in employees' responses to STARA Awareness. LGO significantly alters the relationships between STARA

Awareness and both Knowledge Collecting and Knowledge Donating. Employees with lower levels of LGO tend to exhibit a more substantial decline in knowledge-sharing behavior as perceptions of technological disruption increase. Conversely, employees with stronger learning orientations demonstrate more constructive responses, suggesting that LGO can help sustain knowledge exchange even when technological change is perceived as threatening.

From a behavioral standpoint, LGO may function as an individual psychological resource in technologically disruptive work environments. Employees who perceive that emerging technologies could transform or replace aspects of their jobs may interpret such developments as opportunities to acquire new competencies rather than viewing them solely as threats to employment security. This learning-oriented appraisal can encourage employees to continue seeking and exchanging knowledge. In contrast, individuals with weaker learning orientations may be more vulnerable to withdrawing from knowledge-sharing activities when they experience greater STARA Awareness.

These findings broaden the understanding of the behavioral implications of STARA Awareness by demonstrating that its effects are not uniform across employees and may depend partly on their orientation toward learning and competence development. Employees facing similar technological changes can therefore respond differently according to how they perceive and approach learning opportunities. For technology organizations in Jakarta, fostering a stronger learning-oriented work environment may consequently represent a practical strategy for sustaining knowledge exchange and collaborative expertise development amid accelerating technological transformation.

CONCLUSION

The findings indicate that STARA Awareness has significant negative direct effects on both Knowledge Collecting and Knowledge Donating among technology professionals in Jakarta. Employees who perceive a greater likelihood that STARA technologies could replace aspects of their jobs tend to participate less actively in knowledge-sharing activities. This pattern is consistent with the Conservation of Resources perspective, which suggests that when individuals perceive threats to valued resources such as employment, they may become more inclined to protect and retain their knowledge rather than share it with others.

In contrast, Learning Goal Orientation (LGO) demonstrates positive and statistically significant relationships with both dimensions of knowledge sharing. Employees with stronger learning-oriented tendencies are more likely to seek feedback, develop new capabilities, acquire knowledge, and exchange expertise with colleagues. More importantly, the moderation results indicate that LGO can attenuate the negative relationships between STARA Awareness and knowledge-sharing behavior. The simple-slope results show a pronounced decline in knowledge sharing among employees with low LGO as STARA Awareness increases, whereas employees with high LGO are better able to maintain or even strengthen their collaborative knowledge-sharing activities under conditions of greater technological uncertainty.

The findings concerning the control variables provide additional insights. Generation Z employees showed a positive association with LGO, while Millennials demonstrated a negative association. However, generational membership itself did not have a direct effect on Knowledge Sharing Behavior. Employees working in Software Engineering and Development also exhibited higher levels of LGO, while more frequent use of artificial intelligence was positively associated with LGO. Overall, the results highlight LGO as an important individual-level resource that can help sustain knowledge-sharing behavior among technology professionals operating in rapidly changing technological environments.

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