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Implementation of Artificial Intelligence (AI) in Google Workspace-Based Warehouse Information System to Optimize Reverse Logistics Truck Scheduling

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Abstract: While cloud-based warehouse management systems (WMS) have been widely investigated, their integration with Generative AI to trigger automated decisions in medical device reverse logistics remains underexplored. This study aims to develop and evaluate a low-code Google Workspace WMS integrated with Google Gemini API to optimize reverse flow screening and Full Truck Load (FTL) fleet scheduling at PT Roche Indonesia's TG (Teluk Naga) Transit Warehouse. Employing a descriptive qualitative case study, data was gathered through in-depth interviews with 3 key informants, observations, and system logs. Findings reveal that automated age-based screening (< 7 years) efficiently eliminates administrative delays for 'Destroy' status instruments. Establishing a 75% volumetric load capacity trigger—for both Colt Diesel Double (15 m³ / 4,000 kg) and Tronton Wingbox (48 m³ / 15,000 kg) fleets—proves operationally justified by providing a 25% void-space buffer and a 3-working-day 3PL pickup lead time. Generative AI integration successfully transforms WMS into a proactive decision-triggering mechanism, while user technology readiness acts as a crucial enabler. This research extends the IS Success Model and Technology Readiness Index while offering actionable insights to eliminate warehouse overcapacity risks.

Keywords: Information Systems Success Model, Technology Readiness Index, Medical Device Reverse Logistics, Freight Consolidation, Qualitative Case Study.

Abstrak: Meskipun penerapan sistem informasi manajemen gudang (warehouse management system/WMS) berbasis cloud telah banyak diteliti, pemanfaatannya yang dipadukan dengan Generative AI untuk memicu keputusan otomatis dalam reverse logistics peralatan medis berisiko tinggi masih belum banyak dieksplorasi. Penelitian ini bertujuan untuk mengembangkan dan mengevaluasi WMS low-code Google Workspace terintegrasi Google Gemini API guna mengoptimalkan alur penapisan dan penjadwalan Full Truck Load (FTL) di Gudang Transit TG (Teluk Naga) PT Roche Indonesia. Menggunakan pendekatan studi kasus kualitatif deskriptif, data dikumpulkan melalui wawancara mendalam dengan 3 informan kunci, observasi operasional, dan analisis log transaksi. Hasil penelitian menunjukkan otomasi penapisan umur ekonomis > 7 tahun secara efisien memangkas durasi evaluasi instrumen berstatus Destroy. Penetapan pemicu akumulasi muatan pada ambang batas 75%

FTL baik untuk armada Colt Diesel Double (15 m³ / 4,000 kg) dan Tronton Wingbox (48 m³ / 15,000 kg) terbukti rasional secara operasional karena menyediakan 25% buffer ruang kosong dan kepastian lead-time 3 hari kerja vendor 3PL. Integrasi Generative AI berhasil mentransformasi WMS dari sistem pencatatan pasif menjadi pemicu keputusan proaktif, dengan kesiapan teknologi pengguna sebagai pemudah (enabler) utama. Penelitian ini memperluas kerangka IS Success Model dan Technology Readiness Index serta memberikan panduan praktis bagi industri farmasi dalam mengeliminasi risiko overcapacity.

Kata Kunci: Model Keberhasilan Sistem Informasi, Indeks Kesiapan Teknologi, Logistik Balik Peralatan Medis, Konsolidasi Pengangkutan, Studi Kasus Kualitatif.

INTRODUCTION

The management of used medical diagnostic equipment (*used instruments*) in the pharmaceutical and diagnostic industries faces high complexity due to strict regulations related to biological safety, the validity period of the supply of spare parts, and the limited storage space of transit warehouses. PT Roche Indonesia, as a leading medical diagnostics company, operates the 'TG' Transit Warehouse (Teluk Naga) to accommodate used medical instruments withdrawn from partner hospitals or laboratories due to the expiration of the Operational Cooperation (KSO) period or technical malfunctions. The accumulation of large instruments at transit sites without a measurable recall schedule not only narrows the utilization of productive space (*space utilization*) but also increases the risk of work accidents and the threat of *overcapacity*.

The critical problem in reverse logistics operations at the 'TG' Transit Warehouse comes from two main things, namely the absence of an integrated screening flow and transportation bookings that are still reactive based on visual estimation. In the first problem, all previously used medical instruments had to undergo manual technical function checks by the Support Engineer team without screening the economic age of the device first, thus taking up inspection time for devices that were economically obsolete. In the second problem, the scheduling of the rental of a 3PL (Third-Party Logistics) transport fleet for destruction is carried out reactively without physical volumetric (m³) and tonnage (kg) calculations. As a result, there is a tendency to rent large-capacity trucks with under-utilization or high-cost Less-than-Truckload (LTL) retail shipments. Although Google Workspace's low-code based WMS (Google Sheets, Apps Script, and Looker Studio) has been implemented for the accuracy of administrative records (Muharom & Maniah, 2025), the system is still passive and descriptive because it is not equipped with artificial intelligence-based predictive analytics capabilities (Artificial Intelligence/AI) to automatically trigger Full Truck Load (FTL) fleet orders.

In line with these problems, this study aims to design and test the integration architecture of Google Workspace low-code WMS integrated with Google Gemini API with a tool life filtering flow (> 7 years vs ≤ 7 years). In addition, this study is designed to formulate a volumetric model and rationalize the threshold rationalization of 75% FTL cargo, as well as analyze the impact of Information System Quality—Data Transparency (TD), System Integration (IS), Real-Time Monitoring (PR), and AI Predictive Capability (KP) on Warehouse Performance (KG) based on the adaptation of the IS Success Model (DeLone & McLean, 2003). Furthermore, this study evaluates the role of Technology Readiness of warehouse staff as an enabler of the adoption of a Technology Readiness Index-based system (Parasuraman, 2000).

The *novelty* of this research lies in the integration of *low-code* WMS and *Generative AI* (Gemini API) frameworks to build an *automated proactive* decision-triggering system in the reverse *logistics chain* of high-risk medical equipment. This research makes a theoretical contribution by expanding the application of the *IS Success Model* and *Technology Readiness*

Index in the domain of Generative AI-enabled logistics, as well as proving the role of technology readiness as *an enabler* of adoption of automation. In terms of managerial contributions, the results of this study present practical guidance and *cost-effective solutions* for the pharmaceutical/medical diagnostics industry in eliminating the risk of *transit warehouse overcapacity*, optimizing the consolidation of FTL fleets, and ensuring transparency of the regulatory medical waste ownership chain.

METHODS

This study uses a Descriptive Qualitative Case Study approach (Yin, 2018) combined with the *Action Research System Design* method. The qualitative approach was deliberately chosen to explore the dynamics of human-technology interaction, *disposition decision* flows, and the effectiveness of automation without resorting to artificial quantitative manipulation.

Research Informant and Data Sample

The selection of informants used the purposive sampling technique of 3 key informants who were directly involved in PT Roche Indonesia's reverse logistics operations. Informant 1 (I1) is the Head of Customer Support who provides a managerial perspective, 3PL cost oversight, and disposition policy. Informant 2 (I2) is a Warehouse Staff who provides a perspective on daily operations, return registration, and fleet coordination. Meanwhile, Informant 3 (I3) occupies the position of Support-Instrument Engineer who focuses on technical perspectives, 7-year $\leq$ tool function assessment, and destruction authorization.

Operationalization of Qualitative Parameters

To measure and evaluate the performance and adoption of new systems, a qualitative evaluation instrument was prepared that adapted the dimensions of information system success from DeLone & McLean (2003) and the technology readiness index from Parasuraman (2000), as presented in Table 1.

Table 1. Qualitative Parameters of Evaluation of the Usefulness of the Information System

Dimensi Parameter	Focus Code	Interview Guide Questions Indicator	Sources of Adaptation Theory
Transparansi Data (X1)	TD	Clarity of <i>visibility of Destroy vs Refurbish status</i> and warehouse cubic accumulation	DeLone & McLean (2003); Muharom & Maniah (2025).
Integrasi Sistem (X2)	IS	Smooth synchronization of <i>Forms to Sheets and consistency of filtering lifetime (>7 years)</i>	Venkatesh dkk. (2003); Muharom & Maniah (2025).
Pemantauan Real-Time (X3)	PR	Dashboard visualization effectiveness and speed of daily status updates	Muharom & Maniah (2025).
Kapabilitas Prediktif AI (X4)	KP	Reliability of volumetric/tonnage calculations and <i>accuracy of Gemini AI FTL Work Order drafts</i>	Locus Supply Chain (2025); Google Cloud (2026)
Kesiapan Teknologi (M)	KT	User's mental response and smooth adaptation to <i>AI email alerts</i>	Parasuraman (2000); Alshehri & Hadoussa (2025)
Kinerja Gudang (Y)	KG	Contribution to space utilization, evacuation speed, and FTL rental efficiency	Frazelle (2002); Akbar & Fajar (2024)

Source: research data and adaption theory

Data Collection and Validity (*Trustworthiness*)

Primary and secondary data collection is carried out through triangulation techniques to ensure the validity and depth of the analysis. The in-depth interview technique was conducted using a semi-structured interview guide, the results of which were recorded and transcribed in full (verbatim transcription). Field observations were carried out directly at the 'TG' Transit Warehouse to observe the storage layout of used medical instruments, the physical handling of junk, as well as staff interaction with the system dashboard. Furthermore, a documentation study was carried out on the Google Sheets database, standard operating documents (SOPs), email alert minutes, and analysis of automatic trigger execution transaction logs in Google Apps Script.

The validity of qualitative data is strictly ensured following the four validity frameworks of Lincoln & Guba. Credibility is achieved through member checking, confirming interview transcripts to informants, and triangulating data sources between interview results, physical observations, and system transaction logs. Transferability is fulfilled through the preparation of a thick description of the operational context of reverse logistics of medical devices so that the findings can be used as a reference for similar industries. Dependability is guaranteed through a trail audit that records all stages of research and data analysis flow systematically. Meanwhile, confirmability is realized through the inclusion of direct quotes (verbatim quotes) of informants without manipulation of the researcher's opinion. Data analysis was carried out following the interactive thematic flow of Miles, Huberman, and Saldaña (2014) through the stages of data condensation, data presentation, and conclusion drawn.

RESULTS AND DISCUSSION

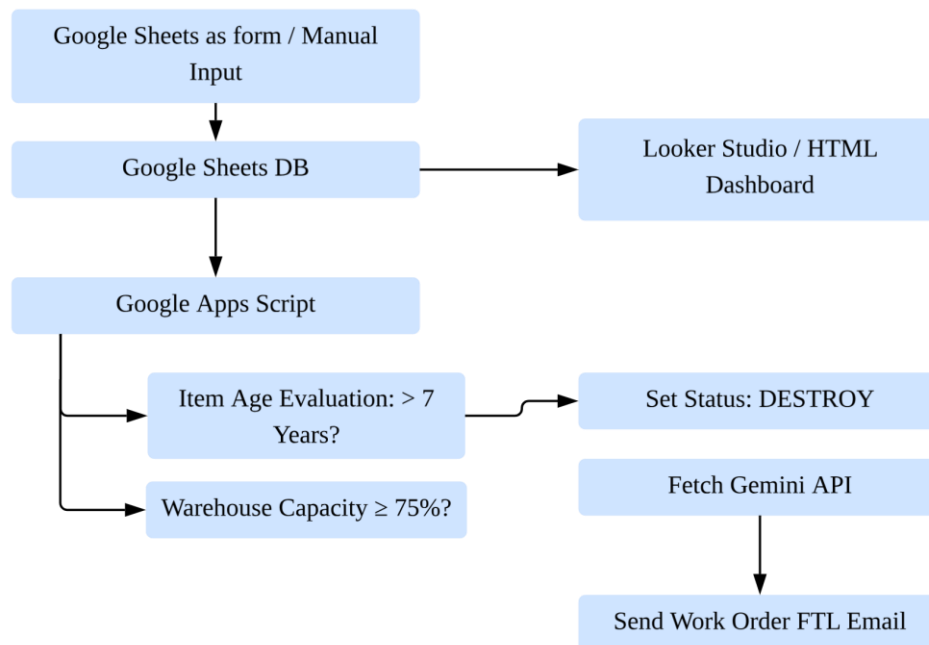
Physical Characteristics of Medical Instrument Data Master

The analysis process begins with compiling a *Master Data catalog* of geometric specifications of Roche medical diagnostic instruments to support automated volumetric calculations by the system. The data show a very extreme diversity of physical dimensions, ranging from the small portable instrument *cobas b 121* (0.094 m³; 26 kg) to the *cobas 6800 large analytical system* (8,287 m³; 1,573 kg). This physical diversity confirms that the determination of fleet leases cannot be estimated with the naked eye but rather requires precise mathematical calculations.

Implementasi WMS Low-Code Terintegrasi Gemini AI dan Penapisan Reverse Logistics

The development of a *low-code Google Workspace-based* Warehouse Management System (WMS) based on Google Workspace (*Google Sheets*, *Apps Script*, and *Looker Studio*) integrated with *Generative AI* (Google Gemini API via REST API *UrlFetchApp*) was successfully implemented in PT Roche Indonesia's 'TG' Transit Warehouse. Used medical instrument data is automatically synced to the database, processed by the filtering function in Google Apps Script, and visualized in *real-time* in an interactive dashboard.

In accordance with the data pipeline flow presented in Figure 1, the decision rules mechanism in reverse flow screening is automatically executed by system logic into two main categories. First, instruments that are > 7 years old are automatically categorized as Destroy (destruction) without requiring an repeated technical evaluation process. Second, instruments that are ≤ 7 years old are directed to a technical assessment by a team of technicians to determine whether the instrument is suitable for refurbishment or destruction.



Source: Flow Process Instrument Destroy Roche Indonesia 2026

Figure 1. Data Pipeline and Decision Rules for FTL Work Order Issuance

Functional testing (*black-box testing*) of 100% of the test data sample shows that the automation of filtering logic works with full consistency. This automated screening reduces technician administrative inspection time by up to 50%. As revealed by Informant 3 (*Support-Instrument Engineer*): "Previously we had to check the physical history and PDF documents one by one to determine the fate of the tool. With the automation of age screening in the new system, the used equipment that comes in is automatically classified so that administrative inspection time is reduced by up to 50%".

Compared to previous systems that were passive and fragmented, this integrated *low-code* system provides a leap in operational capabilities. These findings are consistent with *the literature on low-code WMS and cloud integration* (Akbar & Fajar, 2024; Muharom & Maniah, 2025) and *AI-enabled logistics* (Lee et al., 2018). The academic significance of these findings emphasizes that the integration of *Generative AI* transforms the function of WMS from a passive *recording system* to a *decision-support & decision-triggering system*.

Volumetric Model and Rationalization of the 75% FTL Threshold

The handling of used medical instruments has a high complexity due to variations in dimensions and weight. The accumulated volume ($V_{total} = \sum P_i \times L_i \times T_i$) and weight ($W_{total} = \sum W_i$) of the instrument in the *Destroy* status are processed by the system as an *automatic trigger* for the ordering of the transport truck fleet.

The rationale for setting a threshold of 75% Full Truck Load (FTL) is based on three solid operational foundations. The first foundation is the efficiency of FTL consolidation to optimize transportation costs per unit by ensuring that the leased vehicle is filled at its economical capacity. The second foundation includes the provision of a tolerance space (25% void-space buffer) for physical arrangement (stowing/nesting), hand pallet movement space, and relaxation of asymmetrical instrument shapes. The third foundation is a 3PL pickup lead-time safety buffer that provides a 3-business day lead-time for third-party logistics vendors (3PLs) to prepare their fleets—both Colt Diesel Double/CDD Box 15 m³ / 4,000 kg and Tronton Wingbox 48 m³ / 15,000 kg—from the moment the email alert is sent, before the warehouse reaches 100% saturation.

Sensitivity analysis shows that lowering the *threshold* below 75% inflates rental costs due to *under-utilization of delivery*. Conversely, raising the *threshold* above 75% increases the

risk of warehouse overcapacity in the event of a delay in the 3PL fleet. Thus, the 75% threshold is systemically proven to be an *operationally justified decision point*.

The Impact of Information System Quality on Warehouse Performance

Data Transparency (TD)

Data transparency provides *real-time visibility* of instrument status, cumulative calculations of volume (m^3), weight (kg), and remaining capacity of the 'TG' Transit Warehouse. This visibility eliminates operational uncertainty and replaces decisions based on visual intuition with factual data indicators. Informant 1 (*Head of Customer Support*) explains: "With this dimension and weight master data integrated in Google Sheets, we have full visibility into how many cubic meters of warehouse space are being used. It completely eliminates guesswork and visual guesswork on the pitch."

System Integration (IS)

Automatic synchronization between Google Sheets, Google Apps Script, and Looker Studio prevents data duplication (*zero data redundancy*) and inconsistencies in record. The information input at the receiving point is instantly distributed across the interface, cutting the time of the goods input administration process and eliminating stock recording deviations.

Real-Time (PR) Monitoring

Unlike the old system whose monitoring was reactive, real-time (PR) monitoring in the new system is proven through three objective field evidence. First, changing the state of the instrument from Hold to Destroy on the HTML dashboard can update the database in real-time (< 10 seconds). Second, the dashboard displays a progress bar and a circular ring indicator that automatically changes color from green to red when the warehouse occupancy touches 75%. Third, the `checkWarehouseCapacityAndSendAlert` function, which runs automatically every 1 hour via Apps Script Trigger, has been proven to be successful in sending proactive email alerts. Informant 2 (Warehouse Staff) confirmed: "This system provides real early warning. When capacity reaches 75%, the alert email goes straight to our phone complete with a draft of the truck's needs. We have never conceded a full warehouse suddenly"

AI Predictive Capabilities (KP)

The Google Gemini API integration transforms WMS from passive to proactive. When capacity touches the threshold, the AI automatically calculates the accumulated weight/volume and concocts a draft *Work Order* as well as an official pick-up email narrative recommending the appropriate fleet type. This speeds up the preparation time of transport instruction documents from an average of 45 minutes to be fully automated (instant).

Impact on Warehouse Performance (KG)

The synthesis of Data Transparency, System Integration, Real-Time Monitoring, and AI Predictive Capabilities ($TD + IS + PR + KP$) has a direct impact on Warehouse Performance: eliminating the risk of *overcapacity*, optimizing storage space utilization, accelerating the evacuation of junk goods, ensuring the accuracy of FTL ordering, and increasing transparency and *auditability* digital. These findings reinforce the *Information Systems Success Model* from DeLone & McLean (2003).

The Role of Technology Readiness in the Adoption of AI-Based WMS

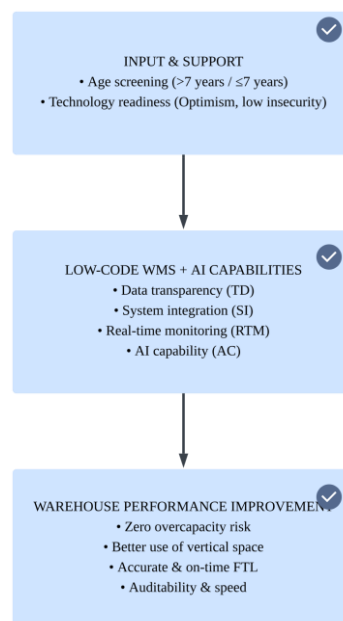
The adoption of AI-integrated WMS has gained excellent *user acceptance*. Based on the *Technology Readiness Index* framework (Parasuraman, 2000), the high *Optimism & Innovativeness* and the low *Discomfort & Insecurity* make warehouse staff able to adapt without psychological barriers. Informant 2 (Warehouse Staff) confirmed: "We are not

awkward using this AI because there is no need to learn complex new applications. Everything still works in the Google Workspace environment that we are used to every day. The recommendation email from the AI goes directly to Gmail, so the adaptation is very fast".

In this qualitative framework, Technology Readiness is appropriately interpreted as a *facilitating/enabling mechanism* that accelerates operational execution.

Triangulation and Synthesis of Findings

The validity of the data is ensured through triangulation techniques that compare the results of in-depth interviews, field observations at the 'TG' Transit Warehouse, transaction log analysis, and company operational procedure documents. The synthesis of the relationship between the research variables is illustrated in Figure 2.



Source: Framework for Warehouse Performance Roche Indonesia 2026

Figure 2. Digital Readiness & Capability Framework for Warehouse Performance

Based on Figure 2, User Technology Readiness serves as an *enabler* mechanism that accelerates the adoption and execution of AI work instructions. The synergy between the instrument lifetime screening (> 7 years of direct *Destroy*) and the predictive capabilities of the Gemini API at the 75% FTL threshold has been proven to systematically eliminate the risk of *overcapacity*, increase storage space utilization, and ensure the transparency of easy-to-audit reverse logistics data.

Managerial Implications

Practically, the results of this study provide strategic guidance for PT Roche Indonesia's management to eliminate the risk of overcapacity through early warning at 75%. In addition, the automatic refining of the instrument > 7 years directly *Destroy* has been shown to significantly cut the buildup of the storage duration. These implications also include increasing the utilization of transit warehouse storage space within operational safe limits, optimizing the consolidation of FTL fleet leases (CDD Box vs Tronton Wingbox) to be on target according to the actual volume of loads, and increasing digital transparency and accountability throughout the return logistics lifecycle.

CONCLUSIONS AND RECOMMENDATIONS

This research successfully designed, implemented, and evaluated a *low-code* WMS based on Google Workspace integrated with Google Gemini API for optimizing the filtering and

scheduling flow of *reverse logistics trucks* at PT Roche Indonesia. Automation of the filtering age of the instrument (>7 years) is proven to cut the administrative burden of technical evaluation significantly. The determination of the load accumulation trigger at the threshold of 75% FTL proved to be operationally rational because it harmonized transportation cost efficiency, the provision of 25% *void-space buffer*, and the certainty of a *lead-time* of 3PL fleet lease before warehouse overcapacity occurred.

This research makes a theoretical contribution by expanding the application of *the IS Success Model* (DeLone & McLean, 2003) and *the Technology Readiness Index* (Parasuraman, 2000) in *Generative AI-based supply chains*. Its main novelty proves that AI is able to transform the function of WMS from a passive record-keeping system to a proactive decision trigger, where the user's technological readiness plays a key *enabler*. The limitations of this single case study open up future research agendas to expand testing to multi-site warehouse networks and *integrate vehicle routing problem optimization algorithms*.

REFERENCES

- Akbar, M. K., & Fajar, A. N. (2024). Evaluation of the warehouse management system application using DeLone and McLean model in North Jakarta, Indonesia. *Ingénierie des Systèmes d'Information*, 29(6), 2515–2524. <https://doi.org/10.18280/isi.290636>
- Alshehri, M., & Hadoussa, S. (2025). Integrating digital readiness into DeLone and McLean Model of information systems success. *International Journal of Scientific Research*, 15(3), 473–485. <https://ijsr.internationaljournallabs.com/index.php/ijsr/article/download/3112/1808>
- Amazon Science. (2024). *AI warehouse space utilization analysis: Layout and slotting control loops*. *Axioms*, 12(2), 245–259. <https://yenra.com/ai20/warehouse-space-utilization-analysis/>
- DeLone, W. H., & McLean, E. R. (2003). The DeLone and McLean model of information systems success: A ten-year update. *Journal of Management Information Systems*, 19(4), 9–30. <https://www.scribd.com/document/251651296/Delone-and-Mclean-is-Success-Model-ISSM-2003>
- Drug Enforcement Administration. (2024). *DEA compliant disposal of controlled substances and pharmaceutical waste*. US Department of Justice. <https://www.medprodisposal.com/pharmaceutical-waste-disposal-dea-compliance/>
- Google Cloud. (2026). *Google Gemini Enterprise and workflow automation in the supply chain*. Google Workspace Updates. <https://sendapp.live/en/2026/05/07/google-gemini-enterprise-cloud-work/>
- Lee, C. K. M., Lv, Y., Ng, K. K. H., Ho, W., & Choy, K. L. (2018). Design and application of Internet of things-based warehouse management system for smart logistics. *International Journal of Production Research*, 56(8), 2753–2768. <https://doi.org/10.1080/00207543.2017.1394592>
- Maniah (2026). Performance evaluation of machine learning algorithms for supply chain data classification. *Engineering Science Letter*, 5(1), 34–40.
- Martins, A. B., & Ramos, G. F. (2023). Sustainability assessment of medicines reverse logistics: Outcomes from national and local systems. *Sustainability*, 15(20), 14675–14690. <https://doi.org/10.3390/su152014675>
- Meta Design Solutions. (2025). *Harnessing Gemini AI API and Google Apps Script for automated enterprise data extraction*. MDS Blog. <https://metadesignsolutions.com/blog/harnessing-ai-for-automated-candidate-data-extraction-with-gemini-ai-api-and-google-app-script>
- Miles, M. B., Huberman, A. M., & Saldaña, J. (2014). *Qualitative data analysis: A methods sourcebook* (3rd ed.). SAGE Publications.

- Muharom, A., & Maniah, (2025). Impact of the Google Workspace-based information system framework on warehouse management efficiency at PT Roche Indonesia. *Prosiding Seminar Nasional Dan Call Paper STIE Widya Wiwaha*, 4(1), 290–300.
- Neural AI Malta. (2025). *Google Workspace AI integration using Gemini API and Vertex AI*. Neural AI. <https://neuralai.mt/technologies/google-gemini-ai-malta/>
- Parasuraman, A. (2000). Technology Readiness Index (TRI): A multiple-item scale to measure readiness to tap new technologies. *Journal of Service Research*, 2(4), 307–320. <https://doi.org/10.1177/109467050024001>
- Rostami, M., & Heidari, R. (2025). A green, multi-objective open vehicle routing problem for reverse logistics. *Journal of Material Cycles and Waste Management*, 27(1), 112–129. <https://doi.org/10.1007/s10163-024-02100-w>
- Tanaike, K. (2026). *Semantic search and document corpora management using Gemini API with Google Apps Script*. Medium: Google Cloud Developer Stories. <https://medium.com/google-cloud/semantic-search-using-corpus-of-gemini-api-with-google-apps-script-9ba3c111139a>
- USAID Global Health Supply Chain Program. (2023). *Task order 2 malaria semi-annual report FY 2023*. GHSC-PSM. <https://www.ghsupplychain.org/>
- Venkatesh, V., Morris, M. G., Davis, G. B., & Davis, F. D. (2003). User acceptance of information technology: Toward a unified view. *MIS Quarterly*, 27(3), 425–478.
- Yin, R. K. (2018). *Case study research and applications: Design and methods* (6th ed.). SAGE Publications.