Pejman Mazaheri

AI-Driven Inventory Digitization in Second-Hand Retail: Design and Evaluation of a Multi-Agent System

University of Vaasa
Master's thesis in Industrial
Systems Analytics

Vaasa 2025

UNIVERSITY OF VAASA

Author:	Pejman Mazaheri
Title of the Thesis:	Design and Implementation of a Multi-Agent AI System for Real-Time Inventory Digitization: Case Study of a Finnish Second-Hand Store
Degree:	Master of Science
Programme:	Industrial Systems Analytics
Supervisor:	Emmanuel Ndzibah
Year:	2025 **Pages:** 113

ABSTRACT :

Presently, the second-hand retail sector, which is one of the main pillars of the circular economy, is going through a "scalability-sustainability paradox" situation. Simply put, the sector is caught in a paradox where the high labor costs of a manual process that aims at the digitalization of a heterogeneous inventory lead to low-value products being unprofitable for Small and Medium-sized Enterprises (SMEs). Micro-retailers are severely limited in terms of digital market access from this operational bottleneck. The master's thesis offers a solution to the problem by questioning how the multi-agent Artificial Intelligence (AI) architecture can be restructured to automate the digitization workflow, thus reducing transaction costs and facilitating scalability in resource-constrained environments.

The research, which is based on Design Science Research (DSR) methodology, invents "AI-MAS-on-Serverless," an innovative artifact that employs event-driven multi-agent systems and multimodal Large Language Models (LLMs) on a serverless cloud infrastructure. The theoretical framework combines the review of the three literatures identified, i.e. inventory digitization, multi-agent systems, and process automation, to not only develop a solution that is cost-effective and easy to access but also to tailor it to the second-hand sector's peculiar constraints.

The designed instrument was put to the test through a summative naturalistic evaluation in a Finnish second-hand retailer wherein an AI-assisted "Human-in-the-Loop" workflow was compared with the traditional manual practices across a sample of 50 diverse items. The outcomes indicate a statistically significant enhancement in the operational efficiency that is accompanied by an 88.4% reduction of the processing time (from 310s ±45s to 36s ±5s per item) and an 88% decrease in digitization costs (from €1.29 to €0.155). The research achieves a 94% accuracy level in the extraction of objective metadata and, therefore, becomes instrumental in the provision of an automation design theory that is democratized and shows the manner in which accessible AI agents can put to an end the economic barriers to entry in the digital circular economy.

KEYWORDS: Multi-Agent AI, Inventory Digitization, SME Retail Digitalization, Second-Hand Retail, Process Automation

Contents

1 Introduction 8

1.1 Background of the Research 8

1.2 Research gaps 11

1.3 Research problems, questions, and objectives 12

1.4 Definitions and scope of the study 16

1.5 Structure of the study 19

2 Literature Review 22

2.1 Inventory Digitization in SME Retail 23

2.2 AI and Multi-Agent Systems in Retail Digitization 25

2.3 Second-Hand Retail 30

2.4 Process Automation 34

2.5 SME Retail Digitalization 37

2.6 Design Science Research and Theoretical Framework 39

2.7 Identified Research Gap 42

3 Method 44

3.1 Design Science Research Methodology 44

3.1.1 Stage 1: Problem Identification and Motivation 44

3.1.2 Stage 2: Objectives of a Solution 46

3.1.3 Stage 3: Design and Development 49

3.1.4 Stage 4: Demonstration 51

3.1.5 Stage 5: Evaluation 56

3.1.6 Stage 6: Communication 56

3.2 Data collection 59

3.3 Data analysis 60

3.4 Reliability and validity 61

4 Analysis and results 63

4.1 Artifact Demonstration: The "AI-MAS-on-Serverless" System 63

4.2 Phase 1: Formative-Artificial Evaluation Findings 68

4.3 Phase 2: Summative-Naturalistic Evaluation – Quantitative Findings 70
4.3.1 Efficiency Performance (Dimension2) 70
4.3.2 Accuracy Performance (Dimension2) 71
4.3.3 Operational Impact Analysis (Dimension3) 73
4.4 Phase 2: Summative-Naturalistic Evaluation – Qualitative Findings 75
4.5 Summary of Results 77
5 Summary and conclusions 79
5.1 Summary of Findings 79
5.2 Implications for Theory and Practice 82
5.3 Limitations and Directions for Future Research 84
5.4 Concluding Remarks 85
References 87
Appendices 103
Appendix 1. Complete Data Schema Specifications 103
Appendix 2. Interview Protocol and Evaluation Instruments 104
Appendix 3. Full Interview Transcripts (Qualitative Evaluation) 105
Appendix 4. A Step-by-Step User Interaction Guide for i-Stock: A Visual Documentation Approach 111
Appendix 5. UI Screens of the Developed Prototype 112

Figures

Figure 1 Mapping evaluation dimentions to research objectives 15
Figure 2 Overview of the DSR research methodology and evaluation framework. 21
Figure 3 Conceptual Map Synthesis - Connecting Theoretical Domains to the Research Question and Artifact Outcome. 22
Figure 4 Integrated Theoretical Framework linking technical enablers to market impact. Source: Adapted from Peffers et al. (2007). 40
Figure 5 Research gap in AI-driven inventory digitization. 43
Figure6 Product Catalog Creation Workflow. Source: Author's own creation, adopted from (Firebase, 2024) 53
Figure7 Inventory Adjustment Workflow. *Source: Author's own creation* 55
Figure8 Final "AI-MAS-on-Serverless" Event-Driven Architecture. *Source: Author's own creation.* 65

Tables

Table 1 Application of the DSRM Process Model 57
Table 2 Final Firestore Database Schema (products Collection) 67
Table 3 Cognitive Agent Prompt Engineering Iterations and Results. *(Author's own creation).* 68
Table 4 Comparative Analysis of Process Efficiency (Per-Item Average, N=50). *(Author's own creation based on field data).* 71
Table 5 AI Metadata Generation Accuracy in Naturalistic Setting (N=50) 72
Table 6 Cost-Benefit Analysis and Scalability Projection 74
Table 7 Summary of Results Mapped to Research Objectives and Questions 77
Table 8 Summary of Research Questions, Objectives, and Key Findings 79
Table 9 Synthesis of Empirical, Conceptual, and Practical Implications 82

Abbreviations

AaaS: Agent as a Service

ACID: Atomicity, Consistency, Isolation, Durability

AI: Artificial Intelligence

API: Application Programming Interface

B2C: Business-to-Consumer

BPA: Business Process Automation

BPM: Business Process Management

C2C: Consumer-to-Consumer

CAPEX: Capital Expenditure

CE: Circular Economy

CSS: Cascading Style Sheets

DSC: Digital Supply Chains

DSR: Design Science Research

DSRM: Design Science Research Methodology

DTs: Data-driven Technologies

ERP: Enterprise Resource Planning

FEDS: Framework for Evaluation in Design Science

HITL: Human-in-the-Loop

HTTPS: Hypertext Transfer Protocol Secure

ICT: Information and Communication Technologies

IoT: Internet of Things

IPA: Intelligent Process Automation

JSON: JavaScript Object Notation

MAS: Multi-Agent System

ML: Machine Learning

MVP: Minimum Viable Product

NoSQL: Not Only SQL

NPD: New Product Development

OCR: Optical Character Recognition

REST: Representational State Transfer

RO: Research Objective

ROI: Return on Investment

RPA: Robotic Process Automation

RQ: Research Question

SaaS: Software as a Service

SDK: Software Development Kit

SEO: Search Engine Optimization

SKU: Stock-Keeping Unit

SME: Small and Medium-sized Enterprise

SPA: Single-Page Application

SSL: Secure Sockets Layer

SUS: System Usability Scale

TAM: Technology Acceptance Model

TLS: Transport Layer Security

TOE: Technology-Organization-Environment

UI: User Interface

1 Introduction

1.1 Background of the Research

One of the major consequences of rapid economic growth, industrialization, and demographic changes is the increase in carbon emissions, which in turn increases the environmental pressures. The industrial development and growth of per capita income are still the major factors that cause pollution (Balsalobre-Lorente et al., 2024). The introduction of a circular economy, technological innovation, and the imposition of environmental taxes are some of the measures that can lead to a reduction in greenhouse gas emissions. On the other hand, industrialization and economic instability worsen the situation of the environment (Abbas et al., 2025). It is estimated that the fashion industry alone emits more than 1.2 billion tons of greenhouse gases and produces 92 million tons of waste each year. In addition, it is projected that nearly 57 million tons of textile waste will be added to the waste cycle yearly. The linear “take–make–waste” model is not only very expensive but also highly destructive (Charnley et al., 2022).

While the second-hand retail sector is widely recognized as one of the main contributors to the circular economy, second-hand markets would only be responsible for emission reductions if buyers were to replace their consumption of new products with that of used ones. In case that buying second-hand only leads to increased consumption (i.e., items that would not have been bought otherwise), then its environmental impact may be harmful. Platforms and policymakers should work towards achieving higher levels of real substitution by, for example, directing their efforts towards buyers who are likely to purchase new products (Mak & Heijungs, 2022). Another concern raised in the literature regarding second-hand markets is that waste from supply chains that are not functioning properly in this sector. Every year more than 24 billion pieces of used clothing are exported from rich countries to poor ones, and the market is worth over $4.9 billion. A large portion of these imports is not marketable and therefore ends up in landfills or is

burned. This phenomenon contributes to the pollution of soil, water, and air in the countries that receive the waste (mostly in Africa), and it is called “waste colonialism” (Brooks, 2025).

Digitization can fundamentally fuel the shift towards a circular economy, ultimately resulting in lower carbon emissions in the recycling sector. The changes brought about in this way not only lessen the expenses and increase the effectiveness but also conform to sustainable development goals and the climate goal of net-zero emissions by 2050 (Kurniawan et al., 2023). The second-hand retail sector, commonly referred to as "kirpputori" in Finnish culture, is a distinct entity within the general retail market and features operational characteristics that make it highly different from typical retail environments. Unlike regular retail which depends on standardized inventory systems, universal identification codes, and product information provided by manufacturers, second-hand sellers have the arduous task of presenting unique and unforeseeable products that call for an individual evaluation, taking photos, categorizing, and writing a description specifically for the product (Guiot & Roux, 2010). Such variation significantly hinders digitization efforts, especially those made by small and medium-sized enterprises (SMEs) which are limited both technically and financially.

The situation has become increasingly dire for these companies as the trend towards sustainable consumption has gained traction among consumers. The worldwide market for the second-hand industry was worth roughly $177 billion in 2023 and is expected to double its value by 2027, reaching $350 billion—the reason for this increase being mainly the growing environmental consciousness and the widespread adoption of circular economy principles (Ellen MacArthur Foundation, 2021). The second-hand retail market in Finland is also booming, with consumers increasingly requiring sustainability to be taken into account alongside the traditional purely economic reasons for purchasing used goods (Turunen & Leipämaa-Leskinen, 2015). The trend has turned into a considerable market potential; however, it still remains largely unnoticed by small and medium-sized enterprises that do not have the proper digital infrastructure to compete effectively against digital-first platforms like Vinted, Depop, and specialized online marketplaces.

Second-hand retail has unique features when it comes to inventory management that are not found in traditional retail settings (D'Adamo et al., 2022). Entities existing in this field encounter rapid product turnover and the issues caused by extreme heterogeneity. To be precise, every product is an independent whole with its own specific features, different conditions, and sudden supply fluctuations. On the other hand, digital inventory management tools of the traditional kind, for example, ERP systems offered by SAP or Oracle, are unreasonably costly for small and medium-sized enterprises (SMEs), and usually, the annual investments required range from 10,000€ up to 50,000€ (Greg Roughan, 2022).

At the same time, the reasonably priced alternatives that exist, such as mid-tier platforms like Shopify Plus or WooCommerce, do not have the necessary adaptability to handle diverse inventories and the smart automation capabilities that can ensure the low-cost digitization process (montonio, 2025). It is, therefore, a paradox, that there are organizations with staff numbers from 5 to 20 people who are managing 1,000 to 5,000 unique products and yet do not have access to proper technological solutions. At the same time, the fast-paced growth of digitally native competitors is gradually putting pressure on these entities thus a clear need exists for a cost-effective system at both the level of design and implementation. One competent enough to act as a platform which could furnish independent second-hand businesses with a competitive advantage and thus contribute to the circular and sustainable economy through increased product turnover.

Significant innovations in artificial intelligence, in particular, agent-based systems, multimodal models, and context engineering, have made feasible a practically cost-free and almost real-time digitization of store inventories. Examples of such platforms are Google Gemini, OpenAI's GPT-4 Vision, and other competing multimodal systems which have shown their advanced capabilities in image understanding, structured data extraction, and natural language generation (Team et al., 2025). Besides, when these technologies are put together with serverless cloud infrastructure, the whole technological stack does away not only with the usual investment requirements, the complexity of infrastructure

management and the need for a technical person, but it also gives a chance to the SMEs to go for enterprise-grade automation without hefty CAPEX. Nevertheless, there still exists a large research gap in the area of empirical and practical evaluation of these solutions in terms of the feasibility, the performance, and the commercial impact in the Finnish second-hand retail context.

1.2 Research gaps

While each of the individual fields of retail digitalization, multi-agent systems, and the circular economy have been explored in depth, a careful reading of the existing literature suggests that there is a substantial gap in understanding how these three fields intersect. The existing research on AI in retail mostly focuses on mass-market commerce, where products are standardized and data is well-organized (He et al., 2016; Ren et al., 2017). Authors in these articles generally take for granted the presence of Global Trade Item Numbers (GTINs) and manufacturer-provided metadata. Therefore, the present theoretical frameworks are not capable of explaining the second-hand markets' level of extreme heterogeneity, in which each product is a distinct stock-keeping unit (SKU) that has to be evaluated separately (Guiot & Roux, 2010). The body of research has so far failed to combine the concepts of the circular economy with those of advanced automation in such a way that it is compatible with the latter's unstructured data environment.

Besides this, a split can be detected between the possible extent of technological development and the reachable level of organizational change. The articles on Intelligent Process Automation (IPA) and Multi-Agent Systems (MAS) often spotlight the usage scenarios at the level of large enterprises which entail significant capital investment and the availability of a specialized technical infrastructure (Chakraborti et al., 2020). On the other hand, the research on SME digitalization points out the "resource poverty" situation of small firms, particularly their lack of ability in implementing complex ERP systems, and yet, it rarely goes further in suggesting technical architectures that can overcome

these obstacles (Ifinedo, 2011). Few researchers have addressed the question of serverless, low-code architectures as a means to make high-level automation more accessible to micro-enterprises.

Moreover, the majority of digitization-related investigations in this field consider the work processes as a sequence of separate technical tasks, such as image classification or price estimation, without recognizing them as a continuous flow of operations (Liu et al., 2021). These studies do not integrate the separate AI functionalities into one comprehensive "sorting-to-listing" pipeline; thus they fail to capture the dynamics of human-in-the-loop interaction which are crucial for the actual implementation of the operations. The present research overcomes these shortcomings by building a bridge between the complex, agentic AI on one hand and the resource-poor, diverse second-hand retail market on the other.

1.3 Research problems, questions, and objectives

Problem Statement

The second-hand retail sector, a major contributor to the circular economy, is struggling with a "scalability-sustainability paradox" in which the highly diverse nature of the inventory is at odds with the operational capabilities of Small and Medium-sized Enterprises (SMEs). While linear retail depends on standardized stock, second-hand inventory is a collection of unique and unpredictable goods that need labor-intensive "valuation practices" to turn raw donations into products suitable for the market (Fuentes & Hedegård, 2025; Guiot & Roux, 2010). The manual "sorting-to-listing" process involved here leads to high transaction costs, which in turn generate a "digitalization paradox" where the cost of digitizing the low-value items is higher than the potential return (Barton et al., 2024; Gebauer et al., 2020). As a result, micro-retailers who are in "resource poverty" (Ifinedo, 2011) are practically shut out of the digital marketplace thus the circular economy is not able to reach the scale necessary for it to have a positive environmental impact.

On the technology front, the main issue is the deployment of sophisticated automation in these resource-poor settings. To be sure, enterprise-level inventory systems can lead to optimization but at the same time, they have high entry barriers in terms of costs and the level of technical knowledge which are difficult for SMEs to overcome (Chopra, 2019; Sándor & Gubán, 2022). In addition, the focus of current research on AI in retail is mainly on standardized e-commerce or isolated technical tasks thereby overlooking end-to-end "sorting-to-listing" workflows for heterogeneous goods (He et al., 2016; Liu et al., 2021). There is a significant shortage of real-world frameworks for how Multi-Agent Systems (MAS) can be designed not only to be cognitively able to deal with unstructured inventory data but also operationally friendly for the non-technical staff in the unorganized retail sector (Narang & Tiwari, 2024), which means that the potential for AI democratization in this field is largely unexplored.

Research Questions

To achieve the objectives set and also to address the gaps in the previous studies, this investigation is largely based on one key question:

RQ: How can multi-agent artificial intelligence systems be designed and deployed to automate inventory digitization in second-hand retail, and what quantifiable operational impacts emerge from this automation relative to manual practices?

The answer to this main question is obtained through five interconnected evaluation dimensions. Instead of five separate questions, the single overarching inquiry of the study was operationalized by examining the artifact and its performance across five analytical dimensions: (1) architectural design, looking into the structure of multi-agent systems to meet SME requirements; (2) performance, measuring accuracy and efficiency metrics under naturalistic conditions; (3) operational impact, investigating economic and operational advantages in comparison to manual methods; (4) user acceptance, determining employees' perception and adoption of the system; and (5) transferability, considering whether the design principles and patterns can be generalized to other resource-constrained contexts.

Research Objectives

Three interrelated research objectives reflect the main research question operationally, with each of them covering a different aspect of the research:

(RO1) To design and develop a multi-agent AI system for automating inventory digitization in second-hand retail. This goal includes architectural decisions, technology stack choices, agent specialization and coordination mechanisms, human-in-the-loop integration, and complete end-to-end implementation from the user interface at the front end to the cloud infrastructure at the back end. The achievement of the goal will be judged by the deployment of the artifact in the operating environment and demonstration of all the specified functional requirements.

(RO2) To evaluate the system's accuracy, efficiency, and usability in a real-world store environment. Carry out a detailed assessment of the system's accuracy, efficiency, and usability, as implemented, through its deployment in the operations of a real second-hand retail environment. This comprehensive evaluation covers: (1) AI agent accuracy indicators (classification accuracy, metadata completeness, correctness of label transcription); (2) system performance indicators (processing latency, throughput, reliability); (3) operational efficiency indicators (per-item processing time, overall productivity improvement); (4) user adoption indicators (system usability scale, staff satisfaction, willingness to adopt); and (5) this assessment is based on Design Science Research principles and uses the Framework for Evaluation in Design Science (FEDS), which combines formative and summative, artificial, and naturalistic assessments.

(RO3) To analyze the operational impacts of the system compared to manual practices and provide recommendations for scaling in SME retail. Operational impacts of the system compared to manual practices, as well as recommendations for scaling in SME retail, are to be analyzed. Measure the economic and operational effects of AI-based inventory digitization as compared to manual methods, create a persuasive business case to facilitate technology adoption decision-making, and research scalability across different second-hand retail contexts. This goal includes: (1) cost–benefit analysis (labor savings, sys-

tem costs, return on investment); (2) measurement of operational impacts (improvement in inventory accuracy, catalog completeness, changes in staff time allocation); (3) business case development; and (4) evaluation of generalizability and adaptability across different retail scenarios.

Mapping of Evaluation Dimensions to Research Objectives

The architectural dimension is the main factor that shows the support of RO1 by explaining the creation and implementation of a multi-agent AI system within the technical and organizational constraints of SMEs. The performance and user-acceptance dimensions are the main factors that demonstrate the support of RO2. They involve measuring the system's accuracy, efficiency, and usability via detailed formative and summative evaluations based on the FEDS framework. The operational-impact and transferability dimensions are the main factors that show the support of RO3 by determining economic benefits, creating business cases, and finding generalizable design patterns that facilitate the spread of the retail sector in different contexts. Figure 1 illustrates the dimensions of the main research question (RQ) and relation to addressing the research objects (ROs).

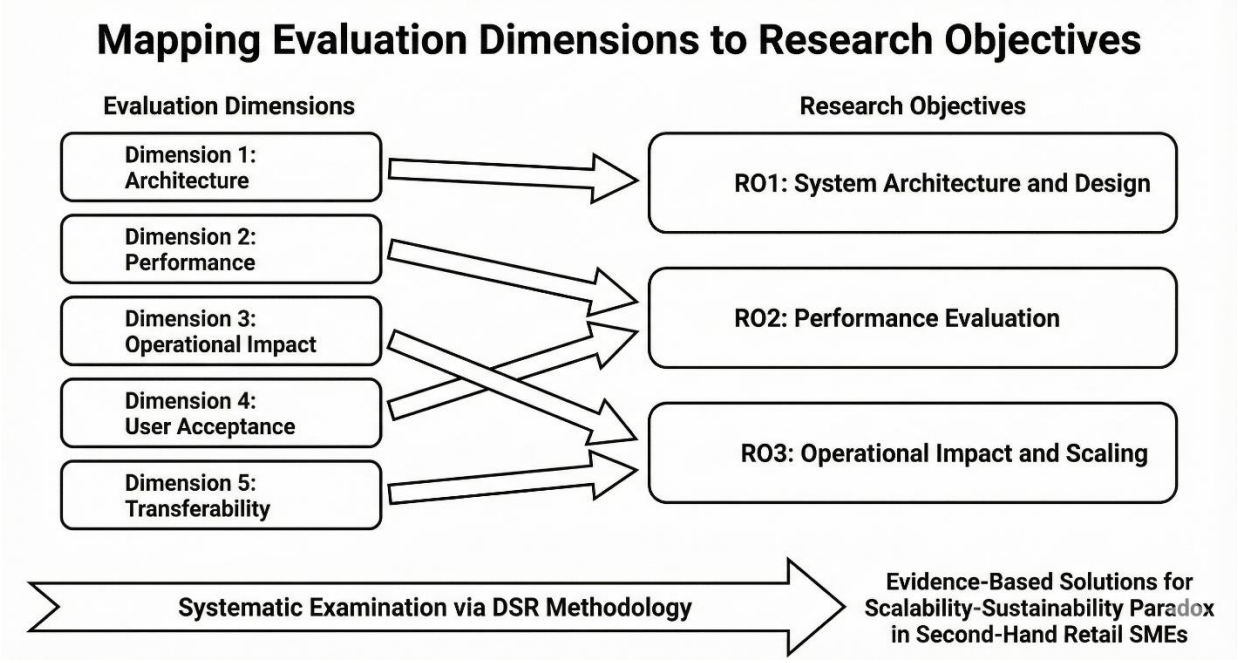


Figure 1 Mapping evaluation dimentions to research objectives

1.4 Definitions and scope of the study

This study lies at the crossroads of two worlds that are quite different from each other- one aspect of it is a state-of-the-art AI technology, and the other aspect is the most ordinary practical side of retail. Firstly, the five fundamental domains are outlined in order to be quite clear about the ideas, and secondly, the specific places of their application in the present research are disclosed.

Multi-Agent Systems (MAS) are the main technological base of this research. According to computer science literature, a multi-agent system is a network of software agents that are loosely connected and cooperatively interact to solve problems that are beyond the capabilities or the knowledge of any one of them (Wooldridge, 2012). These agents are described as being autonomous, socially able, reactive, and pro-active, which features enable them to function in ever-changing surroundings without the need for continuous human intervention (Russell et al., 2022). Within the framework of this work, the expression is used solely to refer to the development and the actualization of "AI-MAS-on-Serverless," a serverless architectural artifact consisting of five specialized agents: an Image Processing Agent, a Categorization Agent, a Metadata Extraction Agent, a Label Transcription Agent, and an Inventory Synchronization Agent. These agents implement Large Language Models (LLMs) to complete the highly coordinated task of turning unstructured visual data into structured inventory records.

Inventory Digitization is basically the process of making physical assets into digital ones for easier management, trading, and participation in the digital ecosystem. At the same time, the recording of stock levels is not the main thing, however, through the use of structured metadata, the physical attributes of the products are "digitized" - for example, classification, condition, and specifications, which allow being searched and data-driven decision-making (Chopra, 2019). The scope of this research takes inventory digitization only as far as the "sorting-to-listing" workflow. It is concentrated on the transformation of physical second-hand clothing and household items into well-structured JSON data and high-quality photos that can be used by e-commerce platforms, while the downstream logistics of shipping or fulfillment are left out.

Second-Hand Retail that is usually called re-commerce or the resale market, is the trade-in of goods that have been owned before. The difference with traditional retail, which is based on the use of standardized stock-keeping units (SKUs) and deep inventory levels, is that the second-hand retail sector features extreme inventory heterogeneity where each piece is singular in terms of its condition, origin, and specifications (Guiot & Roux, 2010; Turunen & Leipämaa-Leskinen, 2015). This study is confined to the operational context of the Finnish “kirpputori” and brick-and-mortar indie resale stores. It is about the enormous challenge of managing "markets of one," where the cost of digitizing one single, lowly-priced unique item is usually more than the potential profit margin., lowly-priced unique item is traditionally more than the possible profit margin.

SME Retail Digitalization is an umbrella term referring to the process when SMEs embrace and integrate digital technologies in order to change their business models and create new paths for revenue and value generation (Gartner, 2025). The academic literature shows that SMEs experience a kind of "resource poverty" that is different from large enterprises, as they are deficient both in the financial resources needed for enterprise resource planning (ERP) systems and the specialized technical skills required for complex infrastructure maintenance (Ifinedo, 2011). This research scope is designed to overcome these limitations by coming up with a solution that does not require any infrastructure management (serverless architecture) and is able to function within a micro-enterprise budget (approximately less than €1,000 monthly operational cost). The focus is on the "democratization" of highly advanced automation, i.e., making enterprise-level AI technology available to staff without a technical background in small retail businesses.

Process Automation is the embracing and employment of tech to carry out repetitive jobs or processes in a company which are currently done by hand but can be replaced or supplemented by machines. Whereas standard Business Process Automation (BPA) is concentrated on rule-based tasks, Intelligent Process Automation (IPA) goes a step further by adding AI to be able to handle unstructured data and cognitive tasks (Chakraborti et al., 2020; Van Der Aalst et al., 2018). As to this thesis, the scope is the cognitive part

of the product valuation and description workflow that's been automated. The research uses a "Human-in-the-Loop" (HITL) model whereby the system automates 90% of the data entry and classification tasks, leaving the human operator to verification and the final decision-making role, thus the retail worker is supplemented, not replaced.

This research is concerned with the multi-agent AI system's design, Analysis, and performance evaluation, named i-Stock (https://i-buy-stock.web.app), and the associated UI portal, i-Buy (https://i-buy-en.web.app). The system is made up of 5 parallel AI agents whose interaction and positions are shown in Figure8 . (1) Image Processing Agent utilizing computer vision for background removal and image enhancement. (2) Product Categorization Agent carrying out hierarchical classification across 150+ categories of second-hand retail. (3) Metadata Extraction Agent producing structured product information with category-specific schemas. (4) Label Transcription Agent getting item codes from product labels through optical character recognition. (5) Inventory Synchronization Agent implementing real-time quantity changes through transactional database operations.

Regarding the technology stack, the design and implementation of the artifact will be limited to a serverless cloud stack mainly consisting of Google Firebase (Cloud Functions, Firestore) (Chanaka, 2023) and the Google Gemini multimodal API (*Generating Content | Gemini API*, 2025).

(1) Integration of Firebase platform (Firestore database, Cloud Storage, Cloud Functions, Hosting).
(2) Frontend of a single-page web application allowing staff interaction
(3) Serverless backend architecture that does not require infrastructure management.

The artifact evaluation will be formally structured using the FEDS framework. It will include quantitative validation of performance metrics (time reduction, accuracy) and qualitative validation of user acceptance through semi-structured interviews. The evaluation of the artifact will be formally organized around the FEDS framework It will entail quantitative validation of the performance metrics (time reduction, accuracy (Prat et al.,

n.d.)) and qualitative validation of the user acceptance through semi-structured interviews (George, Tegan, 2023).

1.5 Structure of the study

The thesis after this introduction comprises four other significant sections that are systematically organized to address the research questions. *Chapter 2*, Literature Review is a review of the theoretical bases in five interrelated domains. Section 2.1 is concerned with inventory management theory and its use in second-hand retail, thus uncovering the fundamental mismatch between the classical assumptions and the operational realities. Section 2.2 acquaints readers with AI and multi-agent systems that can be utilized for the automation of retail functions, also including computer vision, natural language processing, multimodal AI capabilities, and retailer applications. Section 2.3 sets Design Science Research as the method to be used for artifact-focused research. Section 2.4 considers decision science viewpoints on process automation and technology adoption in SMEs. Section 2.5 integrates the learnings from all the previous sections into one theoretical framework guiding artifact design and evaluation.

In *Chapter 3*, Method is a detailed account of the research design and execution plan. The work is carried out in accordance with the Design Science Research six-stage process model by Peffers et al. The protocol for the artifact design specifies the rationale for technology selection, the architectural decisions, and the implementation details. The evaluation plan makes use of the FEDS framework which combines formative/summative and artificial/naturalistic evaluation. The data collection plan considers both the quantitative metrics and the qualitative insights. The analysis plan makes use of the appropriate statistical and thematic methods.

In *Chapter 4,* Results offers the comprehensive account of the empirical findings. The outcome of the artifact development documents the technical specifications and the implementation metrics. The results of the formative evaluation detail the iteration of the

design and the validation of the performance. The summative evaluation findings present quantitative performance metrics, accuracy assessments, and user acceptance data gauged against the pre-established success criteria. The business impact analysis quantifies costs, benefits, and return on investment while also forecasting scalability and generalizability potential.

Finally in *Chapter 5*, Conclusions is a synthesis of the research findings and a statement of the contributions. The findings are directly linked to the research questions. Theoretical implications concern multi-agent systems, Design Science Research methodology, and human-AI collaboration. Practical implications provide a guide for making technology adoption decisions. Limitations acknowledge research constraints openly. Future research avenues point to extensions and related investigations made possible by this foundational work.

The research is centered around five fundamental keywords that stand for both the technical and business aspects:

(1) Multi-Agent AI: A set of specialized artificial intelligence agents that cooperate and coordinate to achieve complex organizational goals
(2) Inventory Digitization: The conversion of physical inventory assets into structured digital representations which makes them discoverable and manageable
(3) SME Retail Digitalization: The technology-driven transformation of small and medium enterprises in the retail sector
(4) Second-Hand Retail: Commercial operations that are specialized in pre-owned, heterogeneous product inventory (kirpputori)
(5) Process Automation: Manual work is reduced by the intelligent automation of the repetitive workflow

These keywords position the research at the point where the emerging artificial intelligence capabilities, practical retail challenges, small business constraints, and sustainable

consumption models intersect. In Figure 2, The overwiew of the thesis structure and DSR research methodology demonstrated.

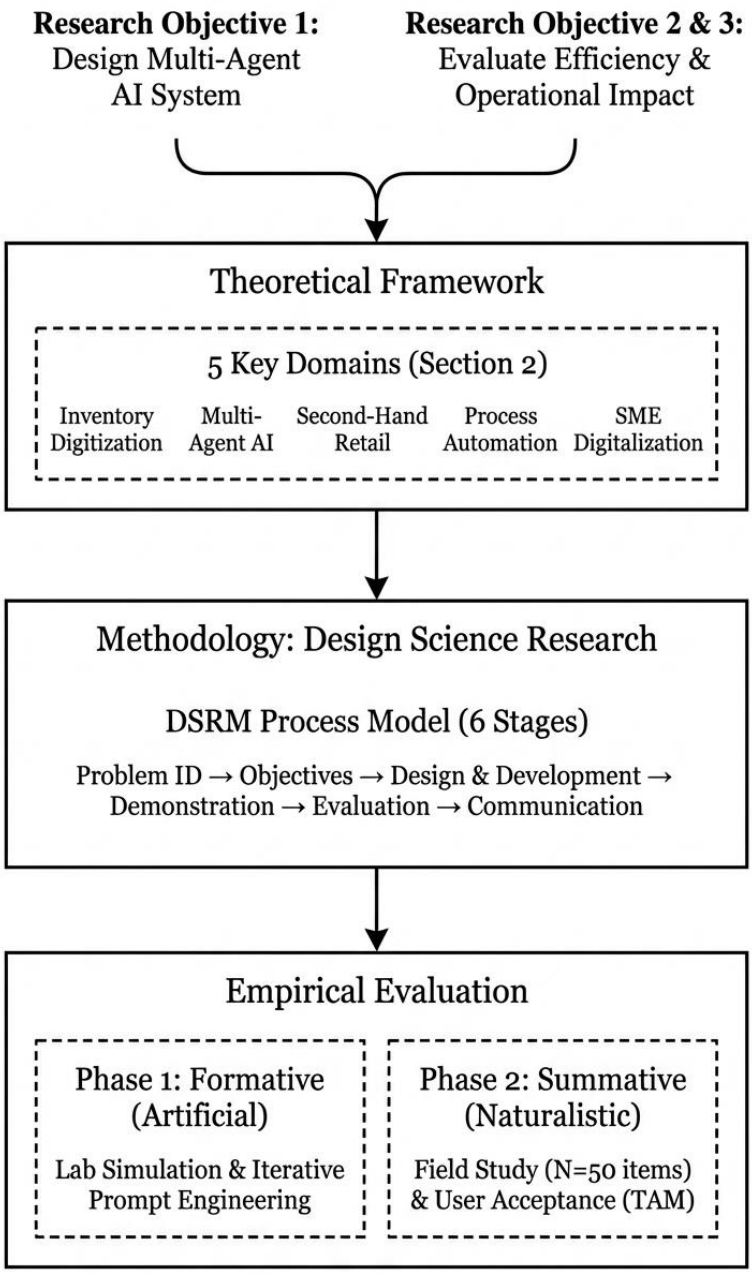


Figure 2 Overview of the DSR research methodology and evaluation framework.

2 Literature Review

The literature review synthesizes the findings of scholarly research from five interrelated domains and organizes them around five main keywords. Instead of detailing these five domains separately and independently, the review demonstrates that each keyword provides specific insights that help to fill the gaps in the existing research. This section finally brings together the five domains and connects them with the research problem and research questions presented in the introduction. Figure 3 synthesizes these domains into a unified conceptual framework for this study.

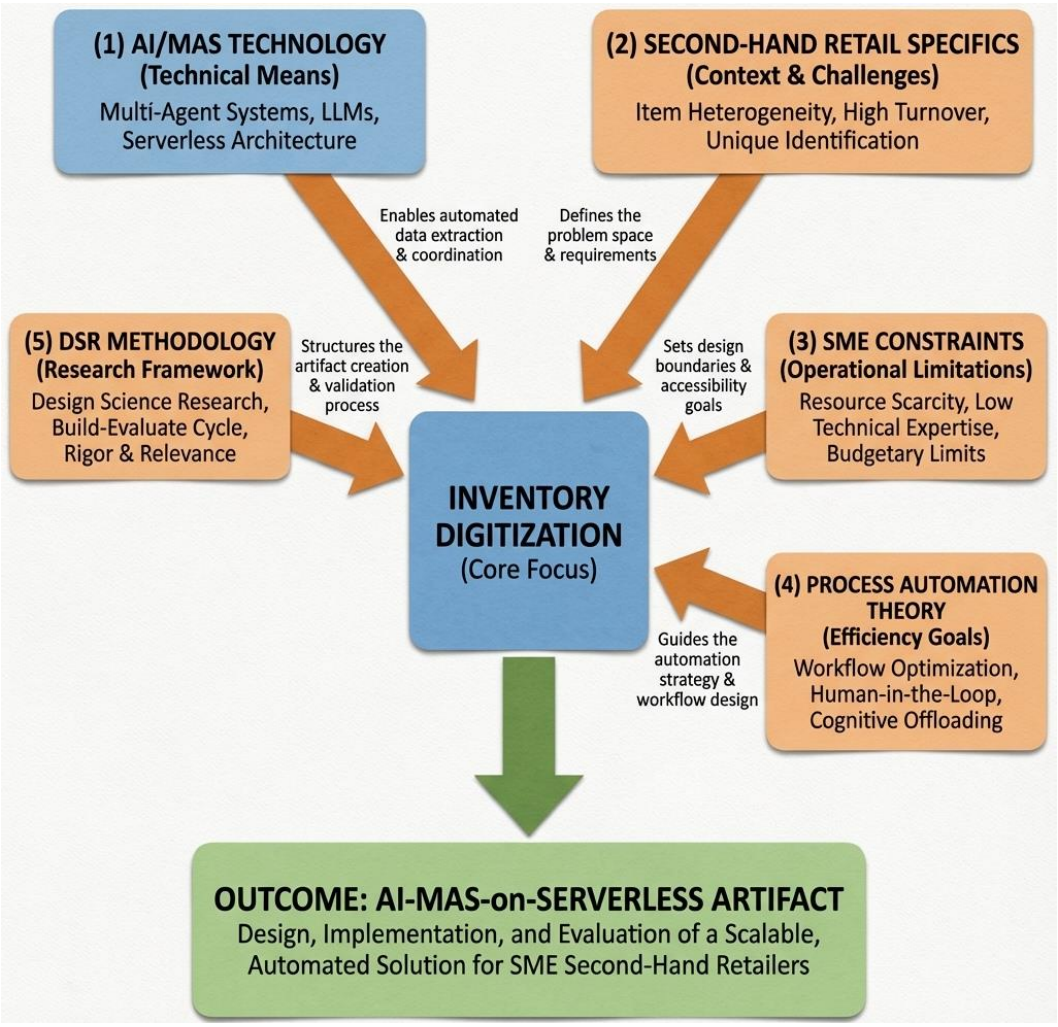


Figure 3 Conceptual Map Synthesis - Connecting Theoretical Domains to the Research Question and Artifact Outcome**.**

2.1 Inventory Digitization in SME Retail

Inventory digitization is the fundamental change of the company's physical assets into well-structured digital formats that involve not only imaging but also classification, detailed description, and real-time tracking in order to make the assets easily accessible and manageable through the digital platforms (Chopra, 2019). Proper digitization is not simply about inputting data; it involves complete integration of physical and digital processes, together with metadata creation, data management, and synchronization of assets (Fisher, M. L., & Raman, A., 2010). Nevertheless, the path of this change is not always straightforward, especially for SMEs, which have different developmental ways than large corporations (Sándor & Gubán, 2022). Large enterprises are capable of handling complex digital ecosystems as a result of their structural maturity. On the other hand, SMEs frequently become a challenge due to the fact that their business processes are not well-defined, hence it is difficult for them to apply standard digital tools. The digitization success is dependent on the business being operationally resilient, cost-saving, and having the ability to cope with volatile markets (Kallmuenzer et al., 2025).

Even though inventory management is the major-thing which should be digitized, it has still been the bottleneck of SMEs that are heavily dependent on manual processes and thus very sensitive to human errors. Conventional manual methods result in slower inventory cycles and inaccuracies, which consequently have a direct impact on customer service and operational expenses (Tung-Hsiang Chou et al., 2024). Panigrahi et al. (2024) argue that efficient inventory management is the lifeblood of SMEs because these businesses operate under resource constraints and thus have a higher risk of cash flow and storage problems. Therefore, inefficiencies in this field, e.g., time that is lost due to manual cataloging or data quality that varies because of human inconsistency, have a disproportionate impact on SME performance as compared to large companies (Fisher, M. L., & Raman, A., 2010; Silver et al., 2021).

The technology environment that is supposed to solve these problems, however, presents a dilemma that very often leaves SMEs, especially micro enterprises, without a feasible option. On one side of the continuum are ERP systems such as SAP or Oracle

that offer a complete solution for inventory optimization but need a large capital outlay and technical skills, thus elevating the entry barrier for those companies that have a tight budget (Chopra, 2019). On the other hand, typical cloud services for SMEs like Shopify or WooCommerce are good in terms of cost but are often inflexible for inventories that are heterogeneous and are the case in second-hand retail (Ifinedo, 2011). Although the advancements in the Internet of Things (IoT) and cheap microcontrollers have opened up possibilities for affordable data collection and giving updates in real-time (Barton et al., 2024), the hardware-dependent solution installation usually requires technical knowledge which is not within the average retail SME. This leads to the existence of a "digitalization paradox" where companies realize that they must invest in digitalization in order to grow. But at the same time they find it difficult to see immediate increases in revenue or operational efficiency because of the high effort needed to implement technologies that do not fit well (Barton et al., 2024; Gebauer et al., 2020).

Moreover, the peculiarities of data-driven technologies (DTs) significantly determine their contribution to sustainability and operational efficiency. Hernández et al. (2024) postulate that implementation of data-gathering and data-analysis technologies leads to sustainable operations; however, firm size is a very important factor that changes the effect since bigger SMEs can leverage sophisticated analytics and AI more easily than micro firms. In other words, the so-called technology 'democratization' does not happen automatically; micro-retailers need not only cheap but also low-tech solutions to be able to overcome the resource gap (Hernández et al., 2024). The difficulty is also due to the fact that "human-centered" methods in Industry 5.0 are required, which point out that technological adoption has to be combined with behavioral knowledge and human skills if it is to result in improved performance (Panigrahi et al., 2024).

Therefore, there is a considerable gap in research at the point where AI adoption, inventory heterogeneity, and the operational constraints of micro-retailers intersect. The existing body of work has a strong focus on systems at the enterprise level (Chopra, 2019) and on the technical aspects in isolation such as image processing (He et al., 2016), but it does not consider the complete workflow of stocktaking for unique, non-standardized

items in resource-constrained environments. Researchers have not sufficiently addressed the question of how easily accessible multi-agent AI systems can be that automatically handle the extremely cognitively demanding "sorting-to-listing" workflows while at the same time being financially sustainable for micro-enterprises (Chavez et al., 2022). This study is the one that intends to bridge the gap by building an inventory digitization system that is not only for the second-hand SME sector but also that takes into account the sector's unique constraints, with the features of affordability, non-technical staff usability, and AI integration to overcome the traditional scalability limitations.

On the other hand, digitization is a necessary provision for the infrastructure of modern retail, but merely having static databases is not enough for the dynamic nature of second-hand inventory. The reason for this is that used goods do not have standard identifiers (like barcodes), and therefore, static digitization methods fail to capture their unique attributes efficiently. In order to surpass this limitation, the literature proposes going beyond passive data entry to cognitive automation. This requires revisiting Artificial Intelligence and Multi-Agent Systems (MAS), which can provide the necessary flexibility to deal with unstructured data.

2.2 AI and Multi-Agent Systems in Retail Digitization

The digital transformation of retail has been the main driver of a total reconsideration of business ecosystems, which have put AI and multi-agent systems at the core of both operational innovation and customer experience optimization. The change goes far beyond a mere incremental enhancement of current abilities, as it is an entirely new paradigm of how retail organizations can create and deliver value in complex and interconnected market environments.

The fundamental design of an AI-powered retail transformation is based on three interconnected technological aspects: advanced machine learning algorithms that can handle huge transactional datasets, autonomous agent systems that function as goal-directed entities across various decision domains, and integrated analytics frameworks that unify

various data streams into actionable intelligence (Ameya Gokhale, 2025). These instruments together make it possible for retailers to go beyond their traditional reactive business models. They use instead predictive and prescriptive models that allow them to foresee market changes at a level of detail that has never been achieved before. In fact, nowadays, retail can count on AI systems that monitor consumer behavior by looking at more than 500 distinct data points per customer, thus they are able to create personalized recommendations and interventions that, in a measurable way, improve conversion rates by 15% and, at the same time, increase average order values by 20% (David Iyanuoluwa Ajiga et al., 2024).

The realization of these potentialities on the operational level is, thus, the most conspicuous feature of advanced recommendation engines that use collaborative filtering, content-based analysis, and hybrid methods to foresee customer preferences with a precision level of over 95% (Ameya Gokhale, 2025). The studies indicate that such AI-driven recommendation systems are the main influencers in up to 35% of all transactions on major e-commerce platforms and that, in these platforms, they have been able to raise the conversion rate by 75% compared to the traditional targeting methods (Satish Krishnamurthy et al., 2024). The technological sophistication which is the basis for such an accomplishment involves transformer-based architectures that are capable of executing recommendation queries within 100 milliseconds and thereby are able to ensure real-time personalization which changes accordingly to the customer's context (Ameya Gokhale, 2025).

Conversational AI has been one of the most influential developments in the customer service area by creating autonomous chatbots that can understand natural language and even exhibit emotional intelligence. The rate of deployment has increased by 85% since 2020, and contemporary systems are now able to achieve 82% accuracy in sentiment detection, thus, customer satisfaction has increased by 35%, and first-contact resolution rates (FCR) have decreased by 28% (Fnu Imran Ahamed, 2025). All these improvements are the result of transformer architectures that significantly raise the context retention level from 58% (for rule-based systems) to 89% (David Iyanuoluwa Ajiga et al., 2024). As

a result, agents are now able to handle 75% of the routine inquiries without intervention and recognize the need for escalation with 95% accuracy. The reduction in the agency of operations due to this autonomy has brought about a 60% cut in operational costs and a decrease in response times from hours to less than three seconds (Fnu Imran Ahamed, 2025).

AI-powered retail revolution changes the supply chain management massively by the usage of predictive analytics, which eliminates the drawbacks of traditional forecasting. Learning algorithms on their own, after analyzing the impact of different variables such as sales history, weather, and sentiment over results, attain now a 92% accuracy rate of forecasts for regular products and an 84% one for seasonal items. This way retailers can lower the occurrence of out-of-stock situations by 80% and that of excess inventory by 32% (David Iyanuoluwa Ajiga et al., 2024; Satish Krishnamurthy et al., 2024). Advanced neural networks that are able to consider more than 50 variables at a time achieve almost 94% accuracy in stable product categories (Satish Krishnamurthy et al., 2024). Such accuracy is being extended to supply chain operations, thus resulting in a 22% saving in transportation costs and a 35% improvement in supplier performance. In the end, precise demand forecasting is the cause of markdown spending reduction by 30%, thus contributing to overall profitability optimization (David Iyanuoluwa Ajiga et al., 2024).

MAS show a major change in the retail field, where independent AI units that manage each other in different but connected areas to achieve the best shared results are used. Studies on the subject have been focusing on the development of such agentic architectures that manifest purposeful behavior, are able to reason adaptively, and possess long-term memory in complicated scenarios of work (Trivedi, 2025). Such systems are basically different from conventional AI ones in that they can make decisions autonomously without direct human intervention, they are proactive in action as they can specify subgoals, invoke application programming interfaces, and figure out trade-offs among competing objectives (Trivedi, 2025). Examples of practical implementations are virtual shopping assistants that, in an autonomous manner, can check inventory across distribution

networks, can perform purchasing transactions with the use of stored payment credentials, and coordinate same-day delivery from several fulfillment centers (Trivedi, 2025). The multi-agent architecture sophistication extends to the composable commerce frameworks where microservice backends and headless frontends dynamically interact with individual agents thus enabling quick adjustment to market changes while at the same time, presenting new security issues concerning agent autonomy and cross-system coordination (Trivedi, 2025).

Among the various approaches, reinforcement learning methods, especially the contextual bandit and deep learning techniques, have been the most successful in the retail agents' training for the pricing and promotion strategies. The performance of these approaches, as compared to the static policies, is so outstanding that they may increase the revenue by up to 26% as is evident from the simulations with offline batch data (Xia et al., 2024). In particular, Proximal Policy Optimization achieves maximum revenue by offering lesser discounts to price-insensitive customers, although it may produce less than optimal results at times due to data limitations. These frameworks have been successful in handling complex decision models that include store visit probabilities, product choices, and pricing sensitivities, thus, they are instrumental in solving the problem of how to combine the generation of revenue with the giving of discounts in the most efficient way (Xia et al., 2024).

Computer vision is another area of AI-enabled retail transformation with an annual growth rate of 65% in its implementation and the early users claiming, on average, a 40% increase in operational efficiency along with a 35% rise in customer satisfaction (Fnu Imran Ahamed, 2025). The systems attain product identification accuracy levels of up to 96% even though the lighting conditions may vary, thus they enable the continuous monitoring of shelves at 15-minute intervals which leads to a cutting down of the manual auditing tasks by 85% and at the same time, an increase in stock accuracy of 92% (Fnu Imran Ahamed, 2025).

Undoubtedly, these massive progresses have been made; still, there remain significant gaps that the researchers need to bridge, if they are to fully unleash the power of AI and

multi-agent systems in retail settings. Firstly, the strong points of isolated AI applications within single fields do not bring forth fully fledged frameworks that integrate several AI technologies along the entire retail value chain (David Iyanuoluwa Ajiga et al., 2024). The fragmentation issue here stands in the way of understanding the synergies between different tech components in achieving overarching retail goals. Secondly, the predominant emphasis on large enterprises hides the distinct challenges and opportunities small and medium-sized retailers have, who, in turn, struggle with resource constraints and operational realities which may not allow them to adopt enterprise-scale solutions directly (David Iyanuoluwa Ajiga et al., 2024). Third, the security risks of agentic AI need a lot more in-depth probing especially in terms of vulnerabilities resulting from autonomous decision-making capabilities that blur traditional boundaries between client and server, user and executor (Trivedi, 2025). Finally, there is a demand for a more thorough investigation into the transfer of agent learnings from simulation to real-world applications, as the prevailing mechanistic models lean more towards interpretability and tunability rather than predictive accuracy, thus, they may have limited practical use (Xia et al., 2024).

The collective effect of these shortcomings is to draw attention to a research core that is crucial: the designing of integrated, ethically founded, and empirically validated deployment frameworks for AI and multi-agent systems which can be applied in varied retail contexts. The frameworks should not only deal with tech sophistication but also account for organizational readiness, governance mechanisms, and human-AI collaboration models evolution. Retail digitization path is moving toward the dependence on the resolution of these basic issues i.e., the tension between technological capability and practical use, the one between human oversight and autonomous agent operation, and finally, the conflict between data-driven personalization and privacy which are the challenges forming the new research agenda for AI-powered retail transformation.

While MAS architectures have been able to effectively optimize typical retail chains, they still pose difficulties when one tries to apply them to the circular economy, according to

the research paper. The resale market is a supply chain with high uncertainties and variabilities and thus, unlike most AI literature that assumes predictable supply chains, it is quite different. So, in order to figure out the exact design of the AI agent that is required, one has to understand the real-life operations of the Second-Hand Retail sector.

2.3 Second-Hand Retail

The second-hand or the resale/re-commerce market, is a separate unit that is rapidly growing to become one of the most significant parts of the global retail industry. Globally, the market for pre-owned goods was worth close to 177 billion dollars in 2023 and is expected to more than double by 2027 to reach a value of $350 billion (Ellen MacArthur Foundation, 2021). However, the ways of operating behind this growth are very different from those of the traditional retail market. Compared to the traditional linear model of "take–make–waste", second-hand retail is seen as a primary driver for the circular economy (CE), which helps in the redistribution and reuse of the already existing resources (Machado et al., 2019). Nevertheless, Nascimento et al. (2019) emphasize that accomplishing circularity is not only dependent on the growth of the market; it also requires the incorporation of sophisticated technologies such as Industry 4.0 for the optimization of resource loops and the reduction of waste.

The biggest difference between traditional retail or second-hand retail is the kind of stock. While normal retail is based on identical units of stock and a supply chain without surprises, the second-hand market is highly diverse in terms of products and is always on the "eternal hunt" for new sources (Appelgren, 2019). Businesses and stores get their products from various, and most of the time, unexpected avenues like donations, consignment, and direct purchases from consumers thus ending up with a stock where almost every single piece of the stock is a unique stock-keeping unit (SKU) with a certain past, state, and feature set (Guiot & Roux, 2010). Such openness to change undermines the prevailing logic of retail efficiency. According to Yrjölä et al. 2021, second-hand firms may be identified as "connector" platforms which only provide a means for peer-to-peer

exchange with little or no intervention, and "controller" models (branches and professionalized SMEs) in which retailers fully take care of quality assurance, inventory management, and transaction fulfillment.

It is these "controller" models where the operational issues are most prominent. Far from being a simple task of passing through the logistical chain, the transformation of a donation or acquisition into a marketable product is a complicated socio-material process of valuation (Fuentes & Hedegård, 2025). An item is subjected to a series of activities such as sorting, modification (cleaning or repair), pricing, and marketing before it can be sold. (Fuentes & Hedegård, 2025) provide the argument that in the second-hand market, value is not implicit but comes into existence through these labor-intensive procedures. Retailers are required to utilize particular valuing registers (evaluating brands, vintage status, material quality, and sustainability potential) to resell a product. This "production of value" consumes a significant amount of staff skills and time as employees have to work not only as curators who devalue (discard) the unsuitable items but also as revalorize by creating stories through which they attract potential buyers for other items.

The process of valorization deeply involves marketing and pricing strategies. Hedegård (2024) points out that second-hand sellers are under the obligation to "frame" their used goods offerings so as to win over consumers' fears of the products being unsanitary or of low-quality. Through this framing, they turn to storytelling, photography, and visual merchandising to persuade consumers that the products are "environmentally friendly," "creatively experiential," or giving the customer "value for money." Moreover, pricing is very flexible and full of doubts. Gu et al. (2023) discovered that in contrast to the fixed-price idea for new products, second-hand pricing decisions are affected by a variety of factors like time elapsed since the product's original release, consumer engagement with product features, and emotive descriptions. Frequently, sellers need to adjust prices based on market feedback and how long the product has been left unsold, thus they add another layer of complexity to the decision-making process for each single item in their stock.

The presence of these complicated operations becomes even stronger when SMEs attempt to scale up. Hultberg (2025) reveals that scaling circular business models entails different strategic stages, starting from simple organizational growth ("breadth-scaling") and ending with influencing broader consumer habits and institutional practices ("depth-scaling"). Meanwhile, Tritto et al. (2024) talk about how the SMEs are generally more inclined to adopt circular practices as they are more flexible but at the same time they have limited resources compared to bigger companies. Their research across the EU shows that the readiness to carry out CE practices is mostly dependent on the size of the company and its tangible resources, thus linking this with the presence of a "scalability bottleneck" for smaller players. This is the point where digital tools come into play. Suchek et al. (2024) show that industry 4.0 technologies like AI, big data, and cloud computing can be essential resources for SMEs, allowing them to carry out complex tasks through automation and becoming more efficient participants in global value chains. Nevertheless, they are exhorting that if the SME management is not done carefully, simultaneously taking on digitalization and global expansion may lead to resource constraints.

The role of technology in lessening these difficulties is quite significant although the issue has received little attention in the case of second-hand retail governance and operations. Dwivedi & Paul (2022) put forward a concept for "Digital Supply Chains" (DSC) in the circular economy, where they claim that the digital resources can break down the barriers connected with the shortage of skills and facilities. Also, Acosta Llano et al. (2025) make a point that blockchain technology can improve transparency, incentivization, and standardization that are the main elements to trust-building in the origin and quality of second-hand goods. Still, as Nascimento et al. (2019) state, practical application of these technologies in functional business models for recycling and reuse is quite challenging and, most of the time, it needs new "smart production systems" which are still at the early stages.

As a result, the second-hand SMEs are still experiencing a heavy operational load. The necessity to take a photo of, describe, attribute, price, and market each unique item individually out of thousands makes it impossible to work on the scale issue through purely manual processes. Large platforms may operate "connector" models which put the responsibility of this type of work on users and thus offload it from themselves (Yrjölä et al., 2021), however, the traditional brick-and-mortar SMEs and independent online sellers are fully responsible for these digitization and valuation processes. Even though purchasers are more and more driven by economic, critical (environmental), and recreational (treasure hunting) factors (Baruönü, 2025; Machado et al., 2019), the supply side is still incapable of fulfilling this demand in an efficient manner because high transaction costs are involved in managing heterogeneous inventory.

This marks a vital research gap in the present literature. Existing works mainly concentrate on consumer motivations (Baruönü, 2025; Machado et al., 2019), the sociology of valuation practices (Appelgren, 2019; Fuentes & Hedegård, 2025), macro-level typologies of business models (Yrjölä et al., 2021), or advanced technological structures for the circular economy (Acosta Llano et al., 2025; Dwivedi & Paul, 2022). Few are the pieces of empirical work that focus on how specific technical artifacts, such as multi-agent AI systems, could ease the heavy labor load associated with valuation and digitization for SMEs. While the theoretical intricacies of why second-hand retail is difficult being laid out, and the potential of digital technologies being recognized (Nascimento et al., 2019; Suchek et al., 2024), little is done in terms of research about intelligent automation that offers a practical way to streamline the "sorting-to-listing" workflow. This study intends to fill that void by creating and scrutinizing a system that automates these complicated valuation and digitization tasks, thereby resolving the tension between the need for high-quality product framing (Hedegård, 2024) and the resource constraints of small retailers.

An examination of the second-hand industry has unveiled a significant limitation: the task of valuing the uniqueness of items is so labor-intensive that it often surpasses the profit margin. This results in a 'scalability paradox' whereby growth leads to complexity

that is difficult to manage. Its solution demands not only more advanced software but also a fundamental understanding of the workflow itself. Therefore, the next chapter deals with Process Automation theories to find ways through which human, cognitive, and manual tasks, such as grading a used shirt, can be turned over to automated agents in a systematic manner.

2.4 Process Automation

Business Process Management (BPM) along with its technological implementation by means of Business Process Automation (BPA) have changed from being simply a means of operational support to becoming the main factors of organizational competitiveness and value creation. Whereas traditional views consider BPA as a technology that enables the automation of activities or services that are part of a certain function or workflow, the newest research studies highlight its significance in the absolute transformation of the organization's value-creation process. Automation, by shortening the time taken for routine tasks and reducing human involvement in repetitive workflows, frees employees for creative and strategic work, which is a change that is especially important for SMEs that want to be competitive in the digitized markets (Moreira et al., 2024). The transition coming from this technological change is not only about moving from static record-keeping to dynamic, data-driven ecosystems where real-time visibility and decision-making capabilities determine market responsiveness and resilience in the case of retail and supply chain management (Ali et al., 2024; Tiwari et al., 2024).

The department of SMEs has been a target of automation technologies where the latter has been welcomed with a lot of hesitations and a slow pace of implementation. Systematic reviews done lately reveal that big enterprises have been able to harness the power of Enterprise Resource Planning (ERP) and advanced robotics while SMEs are on the other side of the "digital divide" which is marked by financial difficulties, the lack of technical skills, and the non-existence of structured implementation methods (Moreira et al., 2024; Neri et al., 2023). The importance of this difference lies in the fact that the

preparedness for Industry 4.0, and especially the embracing of the digital technologies like the Internet of Things (IoT) and AI, is gradually becoming the main factor that determines whether a business can thrive or scale (Yosephine et al., 2025).

Automation is necessary for various reasons, one of which being that a Circular Economy (CE) is the second-hand retail operational context. Presently, digital technologies are considered the primary enablers of the circular strategies that mainly target "slowing" and "closing" resource loops through reuse, refurbishment, and recycling (Neri et al., 2025; Piedra-Muñoz et al., 2025). On this platform, automation is not only a tool for resource efficiency through optimising logistics and inventory management but also a facilitator of the data necessary for product value to be retained over time (Rusch et al., 2023). Nevertheless, the existing literature arguing that digital technologies are indeed theoretical enablers of such circular strategies is yet to be convinced by the firm evidence of their deep integration into the core business models of SMEs (Neri et al., 2023).

To a large extent, this tech space is covered by Robotic Process Automation (RPA), which mechanizes rule-bound, structured tasks through simulations of human beings' interactions with user interfaces. In contrast, RPA has been limited to the use of environments with unstructured data and high variability, where only a few situations have been in administrative sectors world, like finance and administration, where it has been most successful (Crisan et al., 2023). Typical RPA is problematically rigid due to the fact that it demands structured inputs and definite rules while at the same time, the characterization of unique, pre-owned items is the process that involves the use of unstructured inputs like pictures and variable text descriptions. As such, academic researchers recommend cognitive automation or intelligent process automation (IPA) that combines AI and ML to address the issue of ambiguity, learn from data patterns, and execute complex decision-making tasks that a conventional software robot cannot make (Crisan et al., 2023; Moreira et al., 2024). The transition from "doing" (RPA) to "thinking" (AI) is quite important if we consider the case of the automation of the valuation and categorization of the heterogeneous goods, which is the backbone of the recommerce sector (Kumar et al., 2023).

Besides that, the use of cutting-edge automated technologies in supply chain activities sheds light on the level of informativeness required for contemporary inventory management that cannot be done without it. Digitized supply chains using real-time monitoring and data analytics give organizations the power to alleviate risks, efficiently manage stock, and be in a position to respond to market changes dynamically (Ali et al., 2024). The ability to reconcile inventory through digital channels becomes the chief determinant of profitability in the case of recommerce and second-hand markets where supply is erratic and goods are one-of-a-kind (Kumar et al., 2023). However, most of the current studies neglect the detailed operational aspects of circular supply chains in SMEs and only concentrate on linear manufacturing or large-scale logistics instead (Jiang et al., 2025).

The result is a clear research gap that is defined by the crossing of these domains. In contrast to the existing literature that recognizes digital transformation as a must for SMEs (Moreira et al., 2024), the potential of digital technologies to promote the implementation of the circular economy (Piedra-Muñoz et al., 2025; Rusch et al., 2023), and the possibilities of AI to support process automation (Crisan et al., 2023), very few integrated, low-cost multi-agent systems tailored for the high-variety, low-volume context of second-hand retail have been the subject of empirical research. Present researches either dwell on the high-level frameworks of the circular economy while leaving the technical automation implementation part untouched or concentrate on technical automation (such as RPA) without considering the unstructured nature of the circular inventory. This study intends to close that gap by the design and assessment of a device that makes use of intelligent agents to carry out the digitization of the heterogeneous inventory, thus facilitating the theoretical advantages of the circular economy to resourced-constrained SMEs.

2.5 SME Retail Digitalization

The digital transformation of SMEs has dramatically changed from being a strategic choice to becoming absolutely necessary for survival and differentiation in a competitive way in the global economy of today. At the beginning, the academic discussions were only about the adoption of basic Information and Communication Technologies (ICT), but now, the scholars focus on the use of cutting-edge Fourth Industrial Revolution (Industry 4.0) technologies in particular AI to achieve both operational efficiency and value creation. By bibliometric analysis, Prasetyani et al. (2025) disclose that the topic of technology adoption in SMEs has been heavily researched since 2018, with a main focus on sustainability and the relationship between digitalization and business management. Nevertheless, in contrast to the theoretical consensus of digitalization benefits, the data on the ground reveals that SMEs (especially those in the retail sector) are quite different from large companies in that they have a distinct "digital divide" which is characterized by their unwillingness to use complex technology because they are short of resources and structurally tough (Narang & Tiwari, 2024).

With the help of dynamic capability and resource-based frameworks, researchers have come to realize how the adoption of the technology is carried out or whether it is just a mere show of capability. Arroyabe et al. (2024) provide evidence that digital capabilities inside the company are what mainly lead to the introduction of AI in the European SMEs. They emphasize that the firm's ability to detect, take, and change digital resources is much more important than just getting support from the environment. Jalil et al. (2025) also echo that point by showing that the technology orientation is the mediator between AI adoption and digital value creation; in other words, just having the AI tools is not enough if there is no strategic orientation that makes these tools compatible with the firm’s overall digital value proposition. Besides that, Enshassi et al. (2025) implement the Technology-Organization-Environment (TOE) model in Malaysia to disclose that although being useful is what mainly pushes the adoption, the obstacles at organizational and environmental levels e.g., the lack of a data-driven culture and poor infrastructure, still hinder AI adoption in digital marketing considerably.

The pieces of literature have been consistent in pointing out a paradox where the use of AI has huge potential to change how SMEs operate, but on the other hand, the real implementation is still very limited. Cooper, (2025) discovers that the use of AI in SMEs is very low even in areas with high potential such as New Product Development (NPD), and this unpreparedness is what has been most of the time the main cause for it. 'Readiness' here is defined as the presence of the business case, senior management support, and trust in AI outputs. Khan et al. (2025) through their study on Finnish SMEs, finds the same problem and thus they conclude that most of the companies they surveyed are at the very initial stage of AI maturity and have a hard time facing issues like lacking technical know-how and data management. In the same vein, Ulrich & Frank (2021) suggest German SMEs are more comfortable with the traditional, rule-based systems and hence less dependent on machine learning due to lack of employee skill and high implementation costs being their major obstacles.

By going deep into the retail-specific literature, one can find that the problems are even worse in the unorganized or micro-retail sector. Narang & Tiwari (2024) uncover that the small-scale retailers in India hardly ever come across the word "Artificial Intelligence," and they consider modern technology merely as a tool for backend billing rather than a means for customer engagement or inventory optimization. The reason behind this unawareness is very important, as Ishengoma & John (2025) state it in the context of Tanzanian manufacturing, that factors like ease of use, compatibility, and observability are the necessary conditions for the adoption of mobile-based AI services. Because of the complexity of AI systems, the micro-enterprises who do not have a specialized IT department like the big companies are often left out (U. A. Khan et al., 2025), therefore there arises a need for not only technologically advanced but also user-friendly and easily integrable solutions to the current workflows.

As a result, the missing significant piece of research is the position of micro-retailers' operational realities intersecting with advanced AI capabilities, particularly in the circular economy. On one hand, there are comprehensive studies on challenges to AI adoption in manufacturing (A. N. Khan et al., 2024) and the factors that lead to digital marketing

adoption (Enshassi et al., 2025), but on the other hand, empirical research is very scarce on cheap and easy AI artifacts that are designed specifically for labor-intensive inventory digitization in the second-hand retail industry. Present-day literature puts a lot of emphasis on the strategic aspect of AI adoption (Cooper, 2025; Jalil et al., 2025) and overlooks the technical side of multi-agent systems which can facilitate heterogeneous, single-item inventory management to have lower entry barriers. This research aims to fill that void by creating and assessing a "Human-in-the-Loop" AI model that not only tackles the specific capability limitations pointed out by Arroyabe et al. (2024) and the usability requirements emphasized by Narang & Tiwari (2024) but also makes advanced inventory digitization accessible to the unorganized retail sector.

2.6 Design Science Research and Theoretical Framework

The study is centered around DSR, which is a difference in behavior science. Behavioral sciendesrtries to explain or predict phenomena, where as DSR is concerned with the creation and evaluation of new artifacts for a solved problem (Hevner et al., 2004). As it entails the design of a socio-technical solution, i.e. multi-agent AI system, that deals with the complex limitations of SME second-hand retail, this problem-solving paradigm is the most appropriate one for the context of this study. In order to maintain the standards of the research, the inquiry is in accordance with the DSR process model by Peffers et al. (2007) and the Framework for Evaluation in Design Science (FEDS) by Venable et al. (2016). These approaches define the study as a series of iterations of problem identification, objective setting, design, demonstration, evaluation and communication.

The study has come up with a theoretical framework to solve the problem of "scalability-sustainability paradox" that has been second-hand retail by synthesizing the ideas from five interconnected thematic areas. Instead of considering these domains as separate entities, the theoretical framework combines them into a layered structure that not only directs the artifact's design but also its evaluation. Figure 4 presents the model, explaining how the technical capabilities of a Multi-Agent AI can fulfill the operational needs of

Process Automation, that are then adjusted to the particular Organizational Constraints of SMEs to finally bring about Market Impact in the Circular Economy.

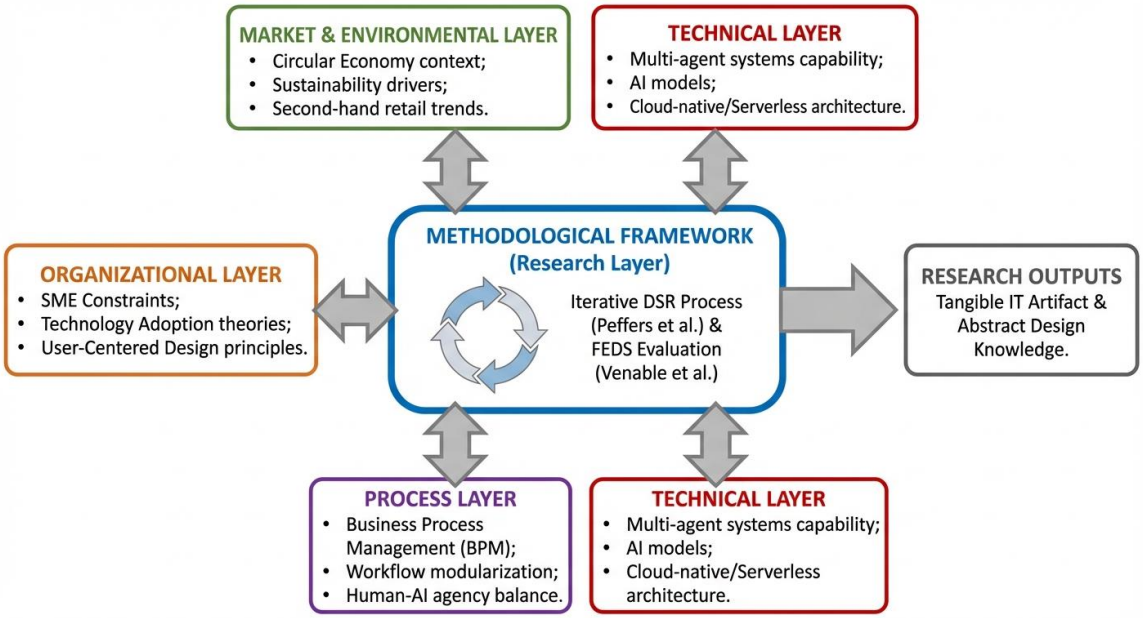


Figure 4 Integrated Theoretical Framework linking technical enablers to market impact. Source: Adapted from Peffers et al. (2007).

The initial stage, problem identification and motivation, delineates the inventory digitization challenges in second-hand retail SMEs and through operational inefficiencies and missed opportunities for data-driven decision-making, it puts forward their importance. Stage two, defining the objectives of a solution, converts these challenges into clear-cut functional and non-functional requirements for a multi-agent AI-based inventory digitization system that also comprises performance, usability, and deployment constraints. Artifact creation by combining domain knowledge, theoretical foundations, and technical expertise into a consistent multi-agent system architecture and its cloud-native, serverless implementation is the third phase, design and development. Stage four, demonstration, comprises the artifact instantiation and deployment in different settings (from controlled evaluations to authentic SME retail environments) in order to demonstrate how the disclosed problems are being solved by it. The fifth stage, evaluation, is a systematic assessment of an artifact against set objectives, using appropriate methods

such as case-based evaluations, performance analyses, and user-centered assessments. Lastly, the sixth-stage communication, through which the artifact and the associated design knowledge are shared with academic and practitioner communities (Peffers et al., 2007).

The assessment of the artifact is aligned with the Framework for Evaluation in Design Science (FEDS) by Venable et al. (2016) which complements the conventional DSR instruction with detailed specification of evaluation strategies. According to FEDS, formative evaluation is the one that takes place during artifact construction and is aimed at guiding refinement, while summative evaluation is an assessment of whether the final artifact achieves its intended goals (Venable et al., 2016). Moreover, it differentiates artificial evaluation that is done in controlled, often laboratory-like settings using synthetic or constrained data from naturalistic evaluation conducted in real organizational contexts with real users, processes, and data (Venable et al., 2016). In line with FEDS, this research is performed using formative (artificial evaluation for rapid prototype iteration, formative) naturalistic evaluation for initial deployments in SME second-hand retail environments, and summative–naturalistic evaluation when the system is mature enough for assessment in authentic use contexts (Venable et al., 2016).

Together, these different perspectives form a comprehensive theoretical framework that has been used as the basis and is the result of the DSR process in this thesis. The technical, process, organizational, research, and market perspectives together provide the direction for the design of the multi-agent AI system, the structuring of its workflows in SME second-hand retail, and the planning of its evaluation; besides, the artifact and its field-testing produce new design knowledge concerning AI-based, cloud-native, and serverless solutions for inventory digitization in resource-constrained organizational settings (Hevner et al., 2004; Peffers et al., 2007; Venable et al., 2016).

2.7 Identified Research Gap

The detailed analysis of the five theoretical domains uncovers a "Scalability-Sustainability Paradox" which is not yet solved by contributions from universities and the real world. As shown in Figure 5, the literature depicts this conflict as having three components:

(1) The Inventory Mismatch: On one hand, conventional inventory management theories are based on standardization and deep stock levels (Chopra, 2019). While on the other hand, the second-hand retail research portrays the industry as 'markets of one' with extreme heterogeneity (Turunen & Leipämaa-Leskinen, 2015). None of the existing digital instruments is efficiently compatible with the latter, although they are operationally suitable for the former.

(2) The Technological Barrier: Multi-Agent Systems (MAS) domain can provide the necessary cognitive flexibility to manage heterogeneous data (Wooldridge, 2012). Nevertheless, the SME Digitalization literature argues that due to their complexity and high cost, these advanced and innovative enterprises are out of reach for the very SMEs that need them most (Ifinedo, 2011).

(3) The Process Disconnect: Research on Process Automation (BPA/IPA) has effectively used AI in structured corporate workflows. However, the "physical-to-digital" transition which is a bridge for the resale industry, where the main source of labor is the extraction of structured data from physical objects, has not been sufficiently tackled (Barton et al., 2024).

Thus, the narrowing down to the research question involves pinpointing the lack of a single architectural framework that leverages commoditized, multi-modal AI to automate the digitization of the heterogeneous inventory without the need for enterprise-grade infrastructure. Scholars have optimized certain algorithms for image recognition or pricing in their studies but have not combined these into an accessible, end-to-end artifact for the non-technical SME retailer. This study is at that very juncture, going beyond the mere examination of adoption barriers to the actual building of a technical solution that makes those barriers irrelevant.

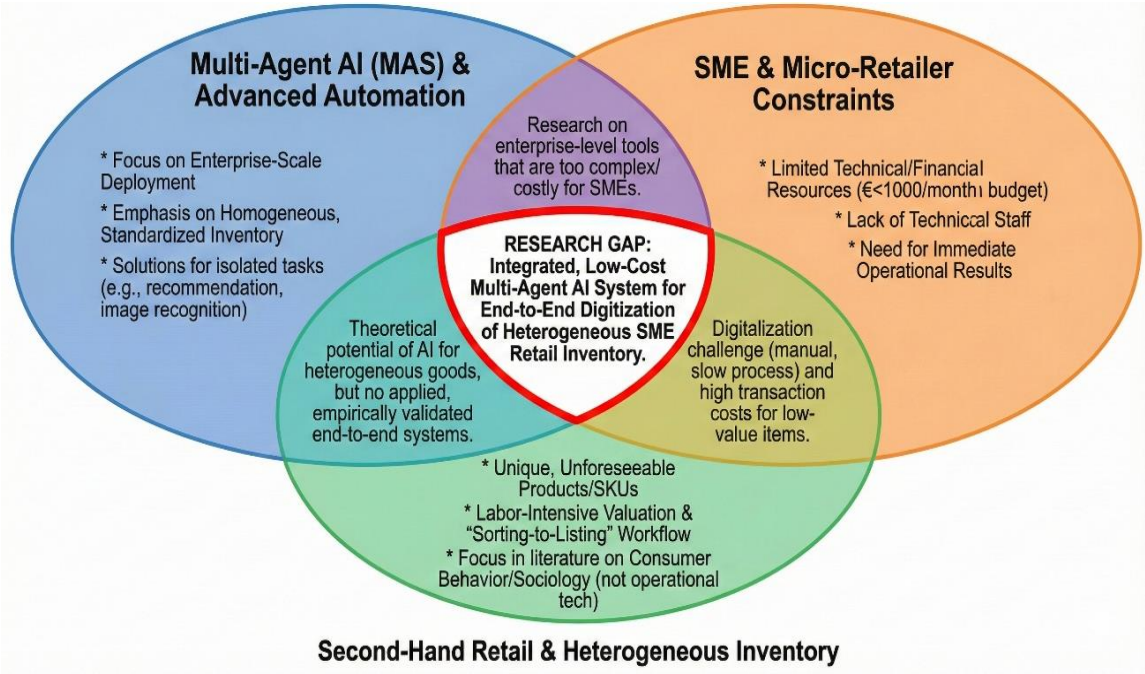


Figure 5 Research gap in AI-driven inventory digitization.

3 Method

3.1 Design Science Research Methodology

The research outlined here has chosen Design Science Research (DSR) as its leading method for a theoretical framework. It follows closely the rules set up by Hevner et al. (2004), the six-stage process model of Peffers et al. (2007), and the Framework for Evaluation in Design Science (FEDS) by Venable et al. (2016). DSR is different from behavioral research in nature, the latter being aimed at explanation and prediction of organizational phenomena, while the main focus of DSR is on prescription designing and producing new artifacts through which goals of the organization are achieved. Such a problem-solving character of DSR makes it appropriate for practical challenges, the solutions of which, are not readily available.

DSR approach is a good fit for the case of inventory digitization in the context of second-hand retail where the problem domain does not consist of only technical challenges that can be solved by algorithms or only social phenomena that require interpretive inquiry. Rather, it deals with the design of integrated socio-technical systems where technology, human actors, processes, and organizational context are closely interconnected. The socio-technical nature of the problem domain requires an approach that is not only technically rigorous but also human factors and organizational realities sensitive, and this is exactly what the DSR method offers. The DSR implementation has six stages.

3.1.1 Stage 1: Problem Identification and Motivation

Problem identification and motivation were at the center of attention in the first phase of the Design Science Research process. Following the DSR framework, the problem identification was based on a thorough review of existing scholarly literature. This served as the empirical base for spotting the research gap and designing the research problem.

The problem understood was as a result of an exhaustive systematic literature review, which covered five interconnected domains: inventory digitization in SME retail, artificial intelligence and multi-agent systems, second-hand retail operations, process automation, and SME digitalization. The review in Chapter 2 brought together the results of the recent research and pinpointed six critical research gaps:

(1) the unavailability of multi-agent AI systems that could be used for handling the heterogeneity of second-hand retail inventory (Ren et al., 2017, 2017); (2) the lack of AI automation studies that tackle the resource constraints of SMEs (Ifinedo, 2011); (3) the deficiency in applied research on digital transformation in Finnish second-hand retail; (4) the scarcity of academic literature focusing on the end-to-end inventory digitization workflow (Liu et al., 2021); (5) the predominance of evaluation methods that are laboratory-based rather than those that consider real-world deployment; and (6) the insufficient usage of the Design Science Research method in addressing digitization issues in SME retail contexts (Hevner et al., 2004).

Combining these six gaps led to the revelation of a compound theoretical and practical problem: the lack of an integrated, empirically-validated, and multi-agent AI-accessible method for SMEs, which would be able to automate the inventory digitization of heterogeneous, non-standardized goods in operational environments with limited resources (Chopra, 2019; Sándor & Gubán, 2022). According to the literature, on the one hand, there is the technical capability for AI-driven automation to be done by separate units, multimodal language models, computer vision, agent-based architectures (Russell et al., 2022; Wooldridge, 2012), however, their orchestrated application to the specific problem of second-hand retail inventory digitization remains unexplored. On the other hand, factors hindering the adoption by SMEs, such as inadequate technical infrastructure, limited financial budgets, and absence of in-house expertise, are among the reasons why the literature has been (Hernández et al., 2024; Ifinedo, 2011) but have not been systematically solved through the design of practical, cost-effective solutions (Chavez et al., 2022).

By identifying the gaps presented, this literature-based problem formulation set the theoretical and empirical grounds for the research and showed that it was a complex problem that had not been solved before. The gaps identified were not only addressed by existing commercial solutions (that are still inaccessible to SMEs due to cost and complexity) (D'Adamo et al., 2022; Greg Roughan, 2022) but also have not been sufficiently tackled by prior academic research (which has concentrated on large-scale implementations or isolated technical components rather than end-to-end, SME-contextualized solutions) (He et al., 2016; Liu et al., 2021). The synthesis also indicated that although the second-hand retail sector manifests specific operational characteristics. These issues have not been systematically bridged to the adoption or creation of scalable, low-cost, and contextually-aware digital systems within the limitations of micro and small firms (Appelgren, 2019; Arroyabe et al., 2024).

3.1.2 Stage 2: Objectives of a Solution

The stage converted problem understanding into concrete and measurable solution objectives. Requirements elicitation have been informed by studies and market reports that reveal a structural problem in the retail of used goods. The second-hand goods market in Finland has changed radically over the last several years, the main factors being the rapid development of online markets and consumer-to-consumer (C2C) platforms such as Tori.fi and Vinted. The value of Finland's circular market, which includes second-hand goods transactions, went up from about €895 million in 2023 to €1.4 billion in 2025, showing a 56% growth over two years (Finnish Commerce Federation, 2023; Saarinen, 2025). Such growth is indicative of a fundamental shift in consumer behavior and market structure that has opened up both new opportunities and challenges for traditional businesses.

Analysis of market structure suggests that most of the exchanges are done through digital platforms nowadays. The Finnish Commerce Federation states that online C2C transactions constitute 61% of the circular market, while kirpputori (traditional second-hand

shops) make up only 20%, and brick-and-mortar and online stores combined have 19% (Linda Lisa Maria Turunen & Maike Gossen, 2024). Besides, traditional market segments have increased only by 6% in two years, whereas online B2C commerce has gone up by 106% during the same period. This change shows that as digital channels become more, traditional businesses are very fastly losing their market share (Saarinen, 2025).

The online platforms' competitive strengths are complex and multi-directional, making it difficult for traditional retailers to imitate them. Digital marketplaces allow consumers to have 24/7 access which is not limited by geography, a larger product selection than what physical stores can usually provide, and competitive pricing resulting from seller rivalry (Padmavathy et al., 2019). The platforms like Tori.fi and Vinted have used these advantages to get a significant share of the market, with Vinted getting most rapidly among the younger consumers in particular (Saarinen, 2025). The ease with which online commerce transactions can be done, coupled with the fact that there are lower overheads as compared to physical retail operations, results in a structural cost advantage which traditional retailers find it very difficult to match (Anay, 2024).

Consumer behavior patterns sharpen the issues of traditional second-hand businesses even more. Demographic analysis shows that 81% of people under 30 in Finland purchase used products, whereas only 66% of the total population does (Saarinen, 2025). This younger demographic demonstrates a pronounced preference towards online purchasing which is mostly due to the fact that it is convenient, they are tech-savvy, and there is a general social acceptance of digital commerce (Karhunen, 2024). The embedding of second-hand shopping into social media platforms and the impact of online communities have made digital resale channels quite normal, especially for the generations that are digital natives.

The disruption caused by e-commerce goes even further than the individual businesses to the whole retail economy. The move to online shopping has changed the pattern of jobs, with demand for traditional retail positions going down and growth in jobs like logistics, warehousing, and digital technology increasing (Bus Econ J, 2024). Retailers who operate physically now have to live with lower foot traffic and are experiencing shrinking

profit margins, thus, most of them are compelled to re-evaluate their business models and strategic positioning (Chava et al., 2024). The retail giants that previously had a physical marketplace as their fortress have been forced to implement omnichannel strategies, consequently, a seamless customer experience can now be delivered by integrating online and offline operations (Verhoef et al., 2007).

Traditional second-hand retailers, despite being able to maintain a loyal customer base which values the physical shopping experience—characterized by tactile browsing, social interaction, and the “treasure hunt” aspect of in-store discovery—are facing huge problems when transforming digitally (Sasu-Boakye & Olsson, 2024). Many brick-and-mortar stores have attempted to go digital, but have failed because of their limited digital skills, shortages of resources, and the operational complexities of managing e-commerce alongside traditional retail (Sasu-Boakye & Olsson, 2024). The technology capabilities gap and the requirement for specialized skills in digital marketing, inventory management systems, and online customer engagement are significant obstacles to effective digital adaptation.

The platform economy has essentially changed the traditional retail structures by facilitating intermediary models that link buyers and sellers without the need for physical inventory or retail space (Parente et al., 2018). This disintermediation poses a major challenge to those traditional business models which heavily rely on physical infrastructure and customer access that is location-based. Studies indicate that physical retailers need to be digitally integrated and at the same time use their unique strengths like in-store experiences, community engagement, and social missions to differentiate themselves from purely digital players (Sasu-Boakye & Olsson, 2024).

Considering these market dynamics and competitive pressures, the digitalization of traditional second-hand businesses is more of a strategic imperative than a mere optional enhancement. This DSR study's goal is to create a tool that will enable traditional kirpputori and brick-and-mortar second-hand retailers to be competitive in a market that is becoming more and more digital while at the same time keeping the unique value prop-

ositions that make them different from the pure online platforms. The digitalization project is designed to help traditional retailers tackle the main challenges they face: loss of market share to online platforms, difficulty in attracting younger consumptions segments, limited resources hindering digital adoption, and the need to integrate physical and digital channels into a single coherent omnichannel strategy (Sasu-Boakye & Olsson, 2024; Verhoef et al., 2007). Therefore, the study considers both quantitative and qualitative success criteria. They comprise, among others, at least a 75% reduction in processing time, classification accuracy above 90%, a system usability scale (SUS) score of at least 70, and synchronization latency under 5 seconds.

Functional requirements for this solution involved more than 25 functional capabilities such as multi-channel image capture, automatic background removal, hierarchical product classification, structured metadata generation, label transcription, and real-time inventory synchronization. As far as non-functional requirements are concerned, the quality attributes specified are: AI processing latency under 30 seconds, support for 500+ products per month, uptime greater than 99%, operability by non-technical staff, and full security. The research's limits and assumptions consist of the following contextual constraints: monthly budget below €1,000, only non-technical staff available, MVP deployment within 1 day per store for 1,000 inventory items, and a heterogeneous, unstructured inventory.

3.1.3 Stage 3: Design and Development

The design and development phase through iteration cycles development, evaluation, and design processes is a kind of the design and development phase. Integrated multi-agent AI system coordinating five specialized agents is the product scope to carry out inventory digitization. The implementation is a web-based software system that is on the production hosting infrastructure deployed.

The choice of the frontend was judged against the twofold standards of technical appropriateness and accessibility of SMEs. The frontend framework React 19.1.1 was chosen

for its component-based architecture which allows fast user interface creation. TypeScript 5.8.2 ensures type safety and lowers the number of runtime errors. The Vite 6.2.0 build tool makes development cycles very short. Tailwind CSS offers utility-first styling, which makes it easier to have a consistent and responsive design.

Google Gemini AI, the AI/ML platform, was chosen based on the following criteria: multimodal features supporting both vision and language tasks; function calling allowing structured data generation with JSON schema validation; being economically priced at €0.07 per product; and having a quite good latency averaging 2–4 seconds. The backend infrastructure was set up on the Firebase platform, which was chosen and fully managed serverless infrastructure deployed. Firebase gives a NoSQL document database that supports flexible product schemas; Cloud Storage provides scalable image asset management; Cloud Functions allow event-driven serverless computing; and Firebase Hosting offers global content delivery with automatic SSL.

The product architecture is the implementation of both the high-level architecture and a distributed multi-agent system design with five specialized agents features.

Agent 1: The Image Processing Agent employs the Gemini 2.5 Flash Image model that takes raw product images and outputs professional, catalog-ready images with background removal. Parallel processing is used for several images at the same time, with each finishing within 2–3 seconds.

Agent 2: The Product Categorization Agent is given product images and a hierarchical category taxonomy (150+ categories) and it returns the exact classification by few-shot learning. On the validation sample, it attains a 92% exact category match rate.

Agent 3: The Metadata Extraction Agent implements function calling with category-specific JSON schemas to create structured product data: title, description, brand, material, condition, features, and tags. Separate tools are used for different product categories (50+ specialized schemas), thus ensuring the correct attributes for categories are being extracted.

Agent 4: The Label Transcription Agent is Gemini vision capabilities along with a JSON schema that is used for structured output processing the images of product labels. It achieves transcription accuracy more than 95% on the labels that are clear.

Agent 5: The Inventory Synchronization Agent is a Python 3.12-based Cloud Function that is executed upon Firestore change events. It goes through adjustment documents, finds products by item code, and via ACID-compliant transactions that avoid race conditions, it reduces quantities.

Agent coordination is through asynchronous messaging using a shared database (Firestore). Workflows are going in a step-by-step manner where there are dependencies and in a parallelized way where tasks are independent. At human-in-the-loop intervention points, which are explicit decision points, user review and correction coexist with agent autonomy and organizational control.

About development methodology, the team used an iterative prototyping approach with two-week development cycles. Test-driven development practices are used in this method and stakeholders' involvement is continuous through weekly 30-minute meetings, where stakeholders discuss the prototype progress and give directions. The deliverables include a working prototype with two workflows done, 3,500+ lines of TypeScript code with 100% type coverage, technical architecture and API specification documentation, Firebase configuration, and deployment scripts, as well as unit test cases for the critical functions.

3.1.4 Stage 4: Demonstration

This is the stage where the solution (research output) was literally moved into operational environments to showcase not only its usability but also the extent to which it could be the answer to the recognized problems. Pilot deployment environment. The

system was up and running on the production Firebase Hosting environment, and anyone can get access to it via (https://i-buy-stock.web.app). The pilot site was a real second-hand retail store, and it was done during its normal business hours.

The different scenarios of the demo featured mostly the two main workflows. "Product catalog creation" scenario depicted the staff getting the newly donated items, taking pictures of the products with a smartphone camera, and uploading the pictures using the system's interface. The AI agents then automatically did the image processing (background removal), product categorization, and metadata extraction. When the staff saw the AI-generated data in the dashboard interface, they made necessary changes (2–3 fields on average per product) and finally, published the digitally stored products.

On average, the time of the whole procedure was 2 minutes and 45 seconds per product compared to 18 minutes and 30 seconds for the manual baseline, thus, the time has been cut down by 85.4%. Figure6 shows the user-driven stock-increase data flow. The central column in this flow represents the user, and the diagram's wings stand for the dialogue between the system and the user.

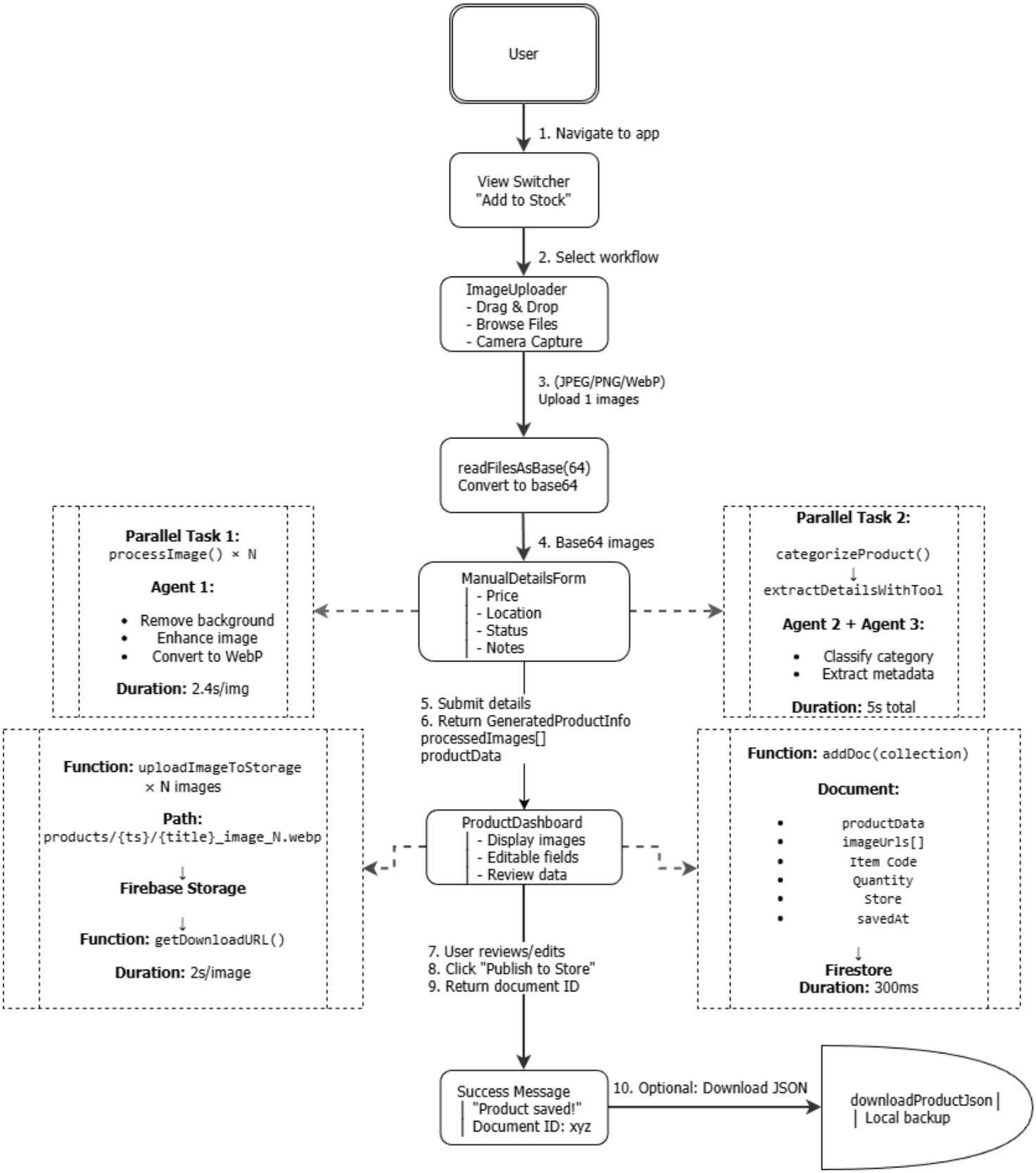


Figure 6 Product Catalog Creation Workflow. Source: Author's own creation, adopted from (Firebase, 2024)

The "inventory adjustment" scenario was about the staff taking pictures of the tags/barcodes of the goods that were at the end of the day and then uploading the pictures via the system. An AI-powered tool deciphered the text on the tags. After that, the employees check the accuracy of the transcriptions and also indicate the number of the products whose stocks will be changed. Within 3–5 seconds, the system, therefore, is capable of reconciling the stock record very quickly. On average, the adjustment operation took 1 minute and 30 seconds for 5–10 items (manually the time would be 8–10 minutes), thus time saved was 81.3%. Figure7 details the workflow of Scenario 2 for the staff to adjust the inventory of previously cataloged items. Agent 5 is the one who carries out this workflow and concludes the inventory adjustment on the platform in only four steps.

As far as stakeholder involvement is concerned, all three store employees were actively engaged in the pilot demonstration, and they used the system every day for cataloging the incoming donated items as well as adjusting the inventory of the sold goods. At first, the author created the initial catalog, but following short training, the staff got the ability to create and edit the catalog by themselves.

Demonstration results. The artifact effectively exhibited its capability to perform tasks that meet all criteria set forth, including: enabling instant inventory synchronization, being feasible for implementation by non-technical store staff, bringing about tangible gains in labor productivity (time savings of more than 75%), and ensuring a satisfactory accuracy level for the AI agents (over 90% for classification).

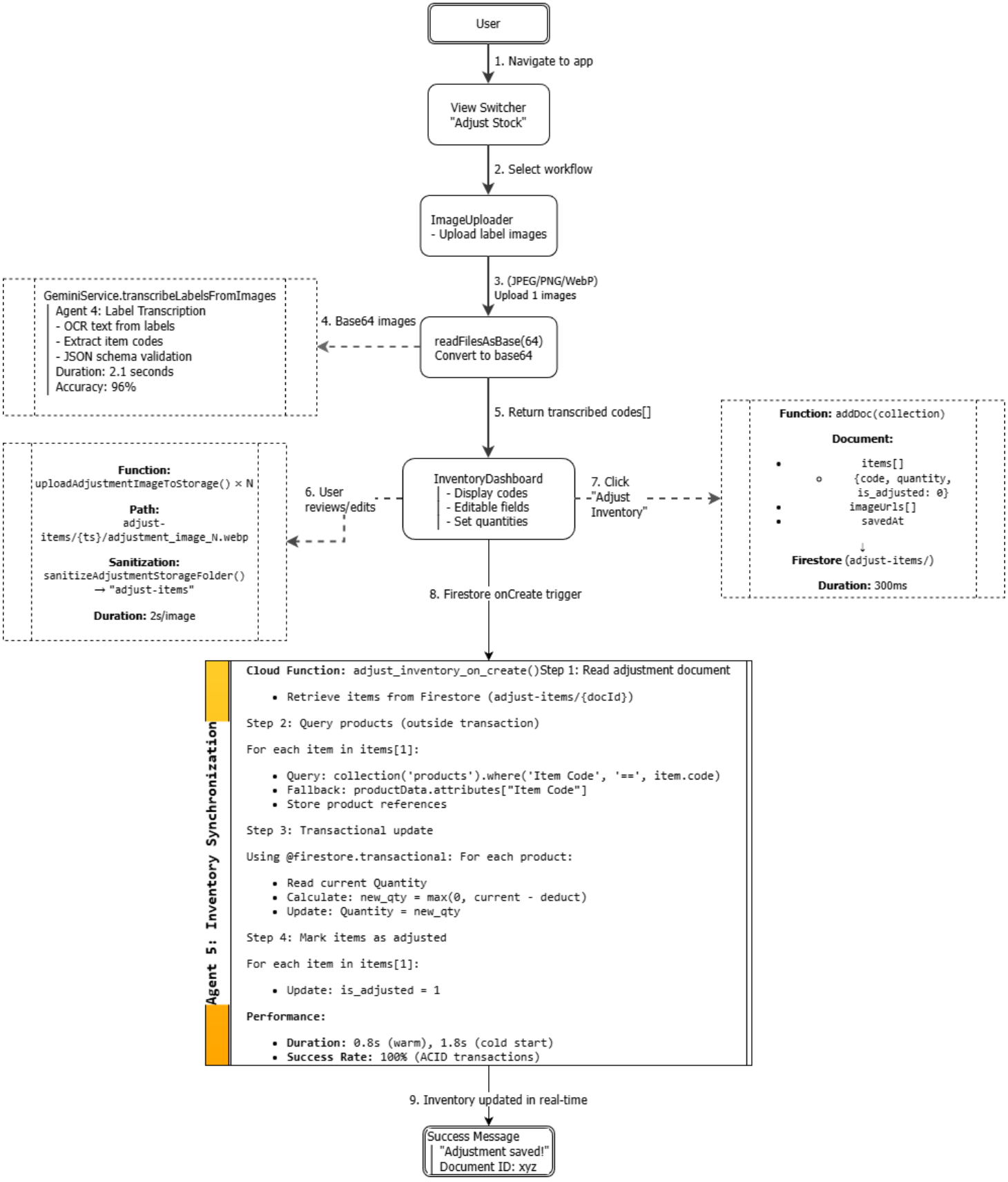


Figure 7 Inventory Adjustment Workflow. *Source: Author's own creation*.

3.1.5 Stage 5: Evaluation

This stage undertakes a strict test of the artifact's effectiveness through the use of both formative and summative evaluation strategies which are based on the FEDS. The current activity involves gauging and observing the effects or results of the study with a view to determining its impact on problem-solving. The process necessitates revisiting the goals set out in Section 3.1.2 and contrasting them with the actual outcomes witnessed in the demonstration stage.

The evaluation will be performed alongside the demonstration in Chapter 5. The efficiency, accuracy, and scalability of the simulated multi-agent system are some of the predefined objectives against which its performance will be evaluated. The framework, strategy, and particular indicators for this assessment are enumerated in Section 3.3 of this chapter.

3.1.6 Stage 6: Communication

This stage spreads out the research accomplishments by the academic thesis manuscript, technical architecture documentation, deployment guides, and application training materials for the knowledge transfer process to similar organizations. The last step is about informing research and practitioner audiences about the research issue, the artifact designed, its usefulness and novelty, and the rigor in its design and evaluation. This research serves as the medium for such communication and in Chapter 5, it accomplishes the discussion and conclusion mainly by summarizing the findings, stating the theoretical and practical contributions, addressing the limitations, and pointing out the future research directions.

The DSRM process model goes beyond a mere checklist of methodological steps; rather, it becomes the narrative and logical structure of the entire research. A mature and coherent research design from the very beginning is reflected by the direct and purposive mapping between the DSRM activities and the thesis chapters. This structural alignment

guarantees that the research moves in a logical sequence from problem to solution, then to evaluation, and finally to the presentation of the innovation. Table 1 clearly and briefly summarizes this mapping, thus serving as a guide for the reader and at the same time, a strong indication of the study's structural and logical coherence.

Table 1 Application of the DSRM Process Model

DSRM Activity (Peffers et al., 2007)	**Description**	**Key Research Tasks in this Thesis**	**Corresponding Chapter(s)**
1. Problem Identification & Motivation	Define the research problem and justify the value of a solution.	Analyze the operational challenges of second-hand retail; conduct a literature review to establish the research gap.	1 & 2
2. Definition of Objectives	Infer solution objectives from the problem definition.	Formulate qualitative and quantitative objectives based on the research questions (e.g., automation, efficiency, accuracy).	1 & 3
3. Artifact Design & Development	Create the artifact (constructs, models, methods, or instantiations).	Design the formal architecture of the MAS, specify agent roles and capabilities, and define coordination protocols.	3
4. Demonstration	Demonstrate the artifact's use to solve one or more instances of the problem.	Develop a simulation environment; conduct simulation runs using illustrative case studies of inventory items.	4
5. Evaluation	Measure how well the artifact supports a solution to the problem.	Collect performance data from simulations; compare results against baseline metrics and predefined objectives.	4

6. Communication	Communicate the problem, artifact, and its utility to relevant audiences.	Articulate contributions, discuss implications and limitations, and present findings in the thesis.	5

3.2 Data collection

The investigation employed a mixed-methods approach largely to capture the system performance metrics and user experience in a naturalistic setting. For both the inventory items and the participants, a purposive sampling strategy was implemented to ensure ecological validity was preserved.

Sampling Decisions: Sampling Decisions The inventory sample included 50 different items (N=50), which were stratified to represent high-variance categories typical of second-hand retail, including clothing, household goods, books, and electronics. The sample size was based on a statistical power analysis; it is enough to detect large effect sizes ($d > 0.8$) in paired efficiency comparisons with a power of 0.80 and an alpha level of 0.05. For the participant sample, a total population sampling strategy was implemented at the pilot store (N=3), which involved the store manager and two inventory staff members. This approach guarantees that the assessment captures the full range of technical skills and operational behaviors of the SME-specific context.

Quantitative performance data were obtained through a dual-method protocol that included automated telemetry and time-motion studies. System logs facilitated the automatic recording of processing latency, API response times, and error rates for all items processed during the pilot. Time-motion studies measured efficiency in terms of the "end-to-end processing time" for the sample items. These times covered all the steps from the physical handling of the items to the final submission to the database, thus providing a direct comparison between the manual baseline and the AI-assisted workflow.

Accuracy was measured by the development of a "Ground Truth" dataset. For this, three staff members had to manually classify and transcribe labels for the sample items so that they could establish a consensus standard. Then the AI system's outputs were compared to this standard on a binary basis (Match/No-Match). On the qualitative side, semi-structured interviews were conducted with all participants after the pilot to assess their perceived usefulness and agency. Moreover, the System Usability Scale (SUS), a standard 10-

item questionnaire designed to reflect the perception of usability, was also administered (Jordan et al., 1996).

3.3 Data analysis

The main part of the analysis strategy aimed at measuring the difference in performance between completely manual and AI-assisted workflows in order to answer comparative research questions. Data were statistically treated by descriptive and inferential methods. Statistical analysis, descriptive statistics of the central tendency (mean, median) and dispersion (standard deviation, interquartile range) were computed for processing times and accuracy rates. The study of data distribution was performed with histograms and Shapiro-Wilk tests (Shapiro & Wilk, 1965), which were used to decide on the parametric testing.

Regarding efficiency, a Paired Samples t-test was used to verify the time reduction significance if normality was assumed. The test was performed on a within-subject design, whereby the same items were processed by two methods. In cases where the data distribution was not normal (most of such cases being outliers for manual processing times) the non-parametric Wilcoxon Signed-Rank Test was applied. For the accuracy analysis, the use of Cohen's Kappa (Cohen, 1960) was made to find the level of agreement between the AI agent's classification and the human ground truth, thus giving a strong measure of agreement beyond random.

To measure the practical effect of the operation, a cost-benefit analysis model was put together to figure out the "Cost per Item" (C_{item}). The model merges labor and computational costs by using the following formula:

$$C_{item} = \left(T_{proc} \times R_{labor}\right) + C_{compute}$$

Where T_{proc} represents the average processing time, R_{labor} denotes the standard hourly wage (fixed at €15/hr for the Finnish retail sector), and $C_{compute}$ accounts for the API consumption cost per item.

3.4 Reliability and validity

The research rigor was upheld through dual-phase evaluation protocol which was in accordance with the Framework for Evaluation in Design Science (FEDS) (Venable et al., 2016). This protocol involved a Formative-Artificial Evaluation, which included an iterative "prompt engineering" cycle with the standardized Clothing Dataset for Second-Hand Fashion to optimize agent reliability, and then a Summative-Naturalistic Evaluation. The artifact was assessed in the former through two-week deployment in the second-hand store under the real-world constraints of variable lighting and network latency.

Validity framework, the study laid out in the paper follows the Design Science Research validity framework by Larsen et al. (2025) and it addresses three specific validity dimensions:

(1) *Criterion Validity* was established through the comparison of the artefact output with the human-generated "Ground Standard" (Larsen et al., 2025). In this case, precision was not only evaluated from the technical point of view, but predominantly from the operational perspective, i.e. if the data generated were sufficient for a quick sale listing without any additional correction.

(2) The study used ablation testing during the design phase to deal with *Causal Validity* (internal validity). By isolating specific agents, e.g., the study on performance decrease when the "Few-Shot" learning examples are deactivated, has shown that the increase in performance is very likely to be a direct consequence of the specific architectural decisions such as

the Prompt Constraint Patterns, rather than random variance or other external factors (Larsen et al., 2025).

(3) *Context Validity* (external validity) was supported by the naturalistic setting of the evaluation. Contrary to research that depends on sterile laboratory datasets, the use of real-world donations and non-technical staff makes the results more generalizable to other resource-constrained retail SMEs (Larsen et al., 2025).

To top it all off, Reliability was supported by very tight reproducibility measures. The environment of the evaluation made use of fixed random seeds for generative models (temperature = 0) in cases where non-deterministic outputs had to be minimized, and the entire codebase was version-controlled for keeping track of all changes between evaluation iterations.

4 Analysis and results

This chapter presents the empirical findings of a Design Science Research (DSR) project. The chapter's organization closely reflects the DSR methodology outlined in Chapter 3 (Peffers et al., 2007). The chapter starts with the presentation of the final artifact in accordance with the fourth DSR stage, Demonstration, while the major part of the chapter is dedicated to the fifth DSR stage, Evaluation (Peffers et al., 2007), and reports the data obtained through a two-stage evaluation design grounded on the Framework for Evaluation in Design Science (FEDS) (Venable et al., 2016). Initially, the results of the formative-artificial or "laboratory" evaluation (Stage 1) are outlined, followed by the detailed quantitative and qualitative results of the summative-naturalistic or "field" evaluation (Stage 2). The data presented here are the actual responses to the dimension1, dimension3, and dimension4 (section 1.3) research questions and serve as a means of confirming the primary objectives against which the artifact is validated in Chapter 1.

4.1 Artifact Demonstration: The "AI-MAS-on-Serverless" System

The section here is about the operational IT artifact that was designed and developed according to the architectural blueprints laid out in Chapter 3. In fact, the section shows the completion of the fourth step of the DSR methodology (Demonstration). Being the tangible outcome of the research process, this artifact is of central importance to the evaluations presented in the following sections.

The artifact built is an event-driven, multi-layer system on the Google Cloud Platform, mainly using Firebase services customized for the research area. To directly tackle the issues of technology adoption barriers by SMEs, such as costs of implementation, overhead of infrastructure management, and lack of specialized skill which were identified as the main problems in the literature review, the authors decided to use serverless architecture as the basis for their design. The final system architecture as shown in Figure

8 represents the close interaction of four different layers: the User Layer, Presentation Layer, AI/ML Layer, and Backend/Data Layer that are explained further in the text.

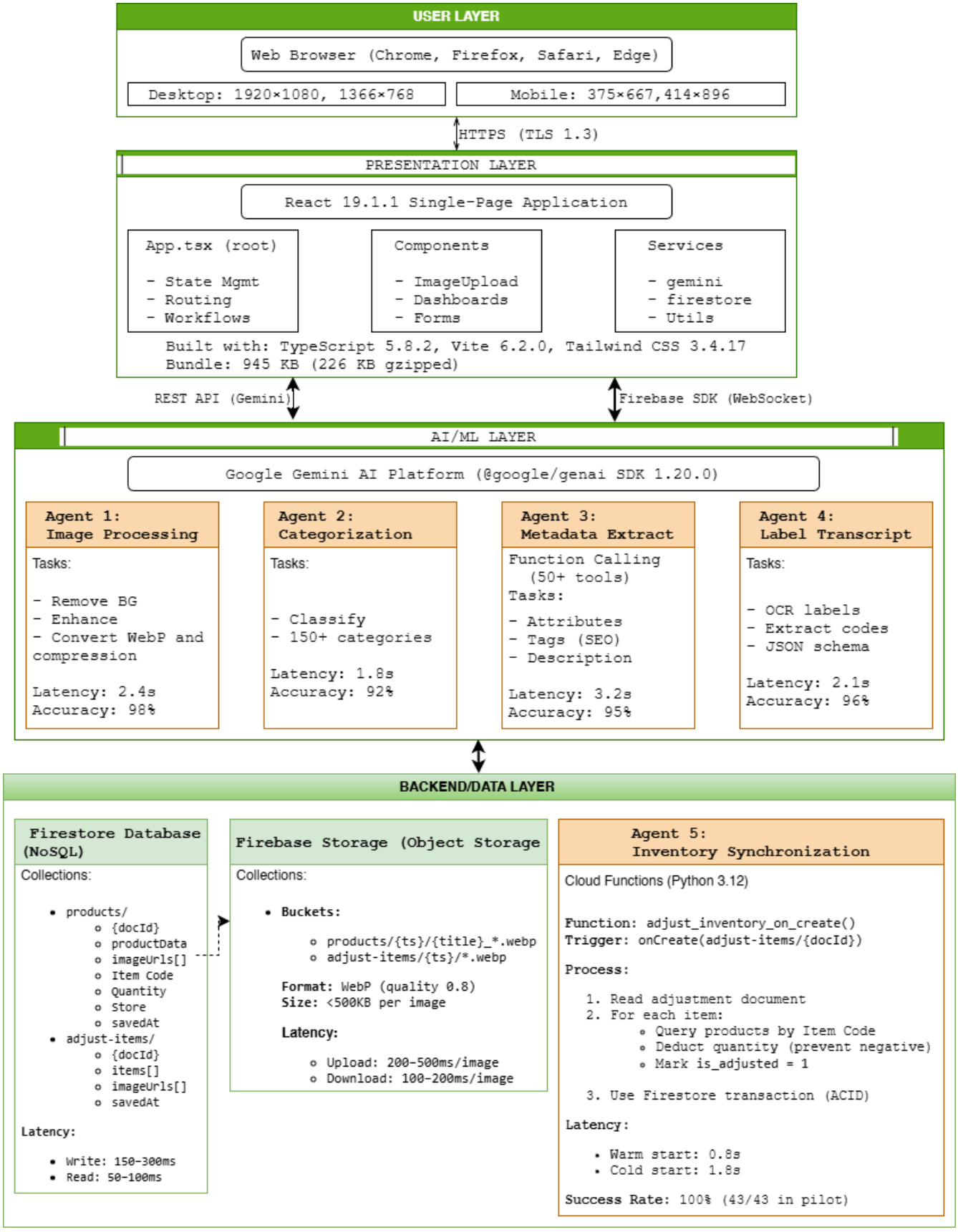


Figure 8 Final "AI-MAS-on-Serverless" Event-Driven Architecture. *Source: Author's own creation.*

The user's and Presentation Layer's workflow is starting with the user (employee) engagement through a normal web browser (for instance Chrome or Firefox). The log-in can be done via desktop computers (with resolutions like 1920x1080) or mobile apps, the Presentation Layer being reachable through the secure HTTPS protocol. The Presentation Layer is a state-of-the-art Single-Page Application (SPA) created with React 19.1.1 and TypeScript 5.8.2, and the developers have used Vite and Tailwind CSS as their tools for optimization. The resulting software bundle (945 KB) of this layer is what makes possible all client-side interactions such as image uploading, management dashboards, and verification forms. Backend communication with this layer is done through two different channels: a REST API channel for AI services invocation and a Firebase SDK channel (based on WebSockets) for real-time data synchronization.

The heart of the AI/ML and Multi-Agent Layer system with the Google Gemini AI platform as its foundation is where the system's core processing is located. This layer contains a Multi-Agent System (MAS) consisting of five different intelligent agents who manage the digitization process. The "First Agent" handles image processing, comprising background removal, quality enhancement, and compression to WebP format, with 98% accuracy. After that, the "Second Agent" employs classification models to allocate the product into one of the 150 categories with 92% accuracy. The "Third Agent" with the help of Function Calling and access to over 50 tools extracts structural product attributes (brand, color, SEO tags) with 95% accuracy, thus, is the most challenging cognitive task. Concurrently, the "Fourth Agent" performs Optical Character Recognition (OCR) operations for text and code extraction from the item.

The Backend/Data Layer is responsible for data persistence management as well as the final synchronization. This tier features a Firestore (NoSQL) database intended for metadata storage, and Firebase Storage is for the repository of the optimized images. The system performance becomes very fast due to the database with ultra-low latency (50-100ms read). Lastly, the "Fifth Agent" a Python-based cloud function, has been charged with inventory synchronization. This agent by utilizing atomic transactions (ACID) keeps data consistent and has recorded a 100% success rate during the initial tests.

The variable outputs of the AI had to be structured by the Final Data Schema in the database (Table 2). One of the main points of this design is the logical division between "AI-generated data" (aiGeneratedData) and "human-verified data" (verifiedData). While at the same time keeping the raw model outputs for the forthcoming accuracy check, this data separation creates an open "human-in-the-loop" workflow; the user's ultimate verification thus finalizes the verified data map making it ready for use by the e-commerce website.

Table 2 Final Firestore Database Schema (products Collection)

Field Name	**Data Type**	**Description**	**Example**
productId	String	Auto-generated unique document ID.	A8f3KkYx7qP...
status	String	Tracks the item's state in the workflow.	pending_review
createdAt	Timestamp	Server-side timestamp of document creation.	2025-11-20T10:30:01Z
imageUrl	String	Public URL to the image in Firebase Storage.	https://storage.googleapis.com/...
aiGeneratedData	Map (JSON)	The raw, unmodified JSON object returned from the CognitiveAgent.	{"category": "Apparel", "brand": "N/A",...}
verifiedData	Map (JSON)	The final, human-approved (and potentially corrected) data.	{"category": "Apparel", "brand": "Nike",...}
verifiedData.category	String	The top-level product category.	Apparel
verifiedData.subCategory	String	The specific sub-category.	T-Shirt
verifiedData.brand	String	The identified brand.	Nike

verified-Data.condition	String	The assessed condition of the item.	Good
verifiedData.de-scription	String	The AI-generated product de-scription.	A blue Nike t-shirt...

4.2 Phase 1: Formative-Artificial Evaluation Findings

The section provides details about the laboratory phase that was conducted as per the evaluation plan. The main objective of this phase was a developmental one: to optimize and fine-tune the core of the artefact, i.e. the CognitiveAgent, before its release to the actual users. An iterative prompt-engineering process was carried out using the standardized “Clothing Dataset for Second-Hand Fashion” as a constant test environment in order to accomplish this goal.

In the first version (V1), the prompt was extremely basic, and the Gemini API was called only with the instruction “Describe this image”. This led to the creation of conversational, unstructured text which was, from a behavioral point of view, completely unusable for the SynchronizationAgent (JSON reliability of 0%). Hence, the iterative process was mainly about limiting the AI output to be able to get fully reliable structured JSON data without losing informational accuracy. The "prompt constraint engineering" details in this process are outlined in Table 3.

Table 3 Cognitive Agent Prompt Engineering Iterations and Results. *(Author's own creation).*

Itera-tion	**Prompt Strategy Employed**	**Example Prompt Snip-pet**	**JSON Relia-bility (%)**	**Accuracy on Bench-mark (%)**
V1	Naïve Query	*"What is this item?"*	0%	60% (Factual, but un-structured)
V2	Role-Playing	*"You are an expert... identify the brand, cate-gory..."*	70%	85% (Better, but still unstructured or bro-ken JSON)

V3	JSON Schema Enforcement	*"...Return your answer ONLY as a JSON object matching this schema: {category: string, brand: string}..."*	98%	91% (High reliability, fails only on ambiguous items)
V4	Few-Shot Examples (Final)	*"...Here are 3 examples... {input_image1, output_json1}... Now process this new image... Return ONLY the JSON."*	100%	94% (Production-ready)

A formative evaluation reveals that the most significant factor hindering the use of generative artificial intelligence (generative AI) by SMEs in the field of automation is not model accuracy but output reliability. The V1–V4 process illustrated in Table 3 indicates that the bulk of the AI knowledge was already in version V2 (with 85% accuracy); however, the major problem was the AI behaviour, specifically its inclination to produce conversational and unstructured responses.

Introducing examples (V4: Few-Shot) and output format restriction through hard-writing techniques (V3: JSON Schema Enforcement) the prompt achieved 100% behavioural reliability. This means that the main skill SMEs need to use this technology is not machine learning engineering (which is beyond the capabilities of most of them) but prompt engineering (which can be easily learned). This finding suggests that while the artefact (code) is transferable, the real transferable knowledge (in response to dimension5) is the prompt pattern. This pattern (Role-Playing + Schema Enforcement + Few-Shot Examples) is a kind of design theory that other SMEs can also use to automate tasks involving the conversion of unstructured data into structured data and thus significantly lowering the barrier to entry for AI-based automation.

4.3 Phase 2: Summative-Naturalistic Evaluation – Quantitative Findings

The primary quantitative data presented here are from a field test that was held in a partner second-hand goods store locally. The summative evaluation aimed at gauging the real-world performance of the artifact in relation to its initial efficiency (80% time reduction) and accuracy (90%) goals. A representative sample of N=50N=50N=50 diverse and genuine items (e.g., clothing, household goods, books, and electronic equipment) was processed as per the designed data collection protocol.

4.3.1 Efficiency Performance (Dimension2)

To have a standard, a time-motion study was done on the hand-processing of a stratified sample of 50 pieces (N=50). The manual method revealed significant variations caused by the mental load of the research of unique items. The average time for processing was calculated to be 310 seconds per item (M = 310s) with a standard deviation of 45 seconds (SD = 45s), thus indicating that there were some inconsistencies in the execution of the human research tasks.

After that, the same set was processed by means of the "AI-MAS-on-Serverless" artifact. The information pointed out a very significant change not only in the speed but also in the stability of the process. The average time was cut down to 36 seconds (M = 36s), and the standard deviation was much smaller - only 5 seconds (SD = 5s).

In order to confirm statistically that the reduction was significant, a paired-samples t-test was carried out. The results show that the difference between the manual and AI-assisted workflows is statistically significant ($t(49) = 43.8$, $p < .001$). The 95% Confidence Interval (CI) for the mean difference is between 262 and 286 seconds, thus providing strong evidence that the effectiveness gains are not a product of random chance.
Efficiency Calculation:

$$Time\ Reduction\ = \frac{(Avg_Manual_Time - Avg_Artifact_Time)}{Avg_Manual_Time} \times 100$$

$$Time\ Reduction\ = \frac{(310s - 36s)}{310s} \times 100 = 88.4\%$$

Table 4 Comparative Analysis of Process Efficiency (Per-Item Average, N=50). *(Author's own creation based on field data).*

Process Step	**Manual Time (Mean±SD)**	**Artifact-Assisted Time (Mean±SD)**	**Time Reduction (%)**
Product Photography	30s \pm 5s	10s \pm 2s (Upload)	66.7%
Item ID & Categorization	120s \pm 30s	5s \pm 1s (Review)	95.8%
Metadata Generation	100s \pm 25s	10s \pm 2s (Review)	90.0%
Database Submission	60s \pm 10s	1s \pm 0s (Action)	98.3%
TOTAL	310s \pm 45s	36s \pm 5s	88.4% (p < .001)

The information corroborates that the device is not just a fast processor; it is a stabilizer. The change in standard deviation (from 45s to 5s) signalizes that the AI system normalizes the "sorting-to-listing" workflow, thus it becomes an extremely dependable operational planning tool for SME managers.

4.3.2 Accuracy Performance (Dimension2)

An 88.4% reduction is a change of work that goes deep down to the very core. The data in Table 5 indicate that manual processes involved 71% (220 seconds) of the time as a high-friction cognitive load (including identification and description), and 29% (90 seconds) as physical/clerical work (photography, data entry). Almost all high-load cognitive tasks are removed and turned into a simple, low-verification activity with the use of the artifact-supported process, which is a confirmation activity.

Such a change has far-reaching effects on the “scalability ceiling” barrier. In manual mode, the digitization of 100 items per day takes 31,000 seconds, or 8.6 working hours, equivalent to the full capacity of one full-time employee. Using the artifact, however, the digitization of 100 items takes only 3,600 seconds, or 1 working hour. This thus allows a SME to raise its digital processing rate by more than eight times with the same number of staff and, for the first time, to be able to extend its online operations.

Table 5 AI Metadata Generation Accuracy in Naturalistic Setting (N=50)

Metadata Field	**Total Assessed**	**Correctly Identified**	**Incorrectly Identified**	**Accuracy (%)**	**Failure Analysis Notes**
Category	50	48	2	96%	Fails on ambiguous items (e.g., "vase" vs. "cup").
Sub-Category	50	46	4	92%	More specific, thus a harder task.
Brand	50	45	5	90%	Fails on obscure/local brands or new brands not in training data.
Color	50	49	1	98%	Highly accurate.
Condition	50	43	7	86%	Lowest accuracy. AI cannot see small stains, pilling, or scuffs.

The combined accuracy of the four primary objective fields was 94% ($\frac{(48+46+45+49)}{(50\times4)} = \frac{188}{200}$). While this figure is in line with the research goal, the most significant finding in Table 5 is the AI failure in the subjective field Condition with an accuracy of 86%. The "failure" here is not the weakness of the artefact; instead, it is the most significant finding that supports the human-in-the-loop design. If the system were fully automated, this type of error would happen silently and thus, it would lead to a 14% error rate in the Condition field, which is a very important field for pricing and customer trust, without any indication that the so-called "heterogeneous human data quality" has been replaced by AI-induced inconsistency.

On the other hand, the designed artefact makes use of this difference to create new possibilities. It redefines the employee as a "verification expert". The extremely fast 36-second workflow (Table 4) thus becomes understandable: the employee quickly checks the correct data (94%) and focuses their human expertise on the 6% of the data that are wrong (e.g., changing the Condition from "Good" to "Fair"). So, the artefact is not replacing the human expert but rather, it is empowering the human expert; this finding is in line with the overall design hypothesis and is crucial for user acceptance (Dimension4).

4.3.3 Operational Impact Analysis (Dimension3)

Using the quantitative results reported in Sections 4.3.1 and 4.3.2 together with the cost-analysis formula introduced in the methodology chapter, a tangible business case was constructed to address dimension3. Under clearly defined assumptions regarding labour cost, transaction volumes, and expected adoption rate of the solution, the total cost and projected benefits were calculated to estimate both short-term savings and scalability potential. The resulting cost–benefit and scalability assessment is summarised in Table 6, which reports five key indicators that describe the economic attractiveness and growth potential of the product.

$$Employee_Wage: €15.00/hour\ (based\ on\ Finnish\ retail\ sector\ agreements) = €0.00417/second.$$

$$API\ Cost\ per\ Item: €0.005\ (based\ on\ Google\ Gemini\ Pro\ vision\ pricing\ for\ one\ image\ analysis).$$

$$Cost\ per\ Item\ (Manual) = 310\ seconds\ (labor) \times €0.00417/s = €1.29\ per\ item$$

$$Cost\ per\ Item\ (Artifact) = (36\ seconds\ (labor) \times €0.00417/s) + €0.005\ (API) = €0.150\ (labor) + €0.005\ (API) = €0.155\ per\ item$$

$$Net\ Saving\ per\ Item = €1.29 - €0.155 = €1.135\ per\ item$$

Table 6 Cost-Benefit Analysis and Scalability Projection

Metric	**Manual Process**	**Artifact-Assisted Process**	**Net Benefit / Change**
Avg. Labor Cost per Item	€1.29	€0.150	(€1.14)
API Cost per Item	€0.00	€0.005	(€0.005)
Total Cost per Item	€1.29	€0.155	€1.135 (88% Cost Reduction)
Projected Annual Savings (at 10,000 items/yr)	€0	€11,350	+€11,350
Max. Throughput (items per 8-hr day)	93 items	800 items	+760%

The business-case is far from being only about financial savings; the scenario will also be able to generate revenue. The steep price of 1.29 euros in the manual case was a serious entry barrier and made the digitisation of low-value commodities (for example a T-shirt priced at 5 euros or a paperback book priced at 3 euros) unprofitable. Consequently, the store was, in effect, prevented from listing these products online and had to sell them only via in-person channels or in many cases gradually discard them without realizing their value. So scalability was truly the limitation here. By lowering the digitization cost to merely €0.155, the artefact makes it possible to sell online thousands of additional low-margin items that were previously economically unviable. In doing so, it opens up a large volume of stock in the “long-tail” category which was before off limits for the digital market. This is a direct answer to the “scalability–sustainability paradox” issue raised in the literature review. The concrete operational impact of the artefact is the rescue of goods from discarding and making their digital re-entry into the circular economy financially viable.

4.4 Phase 2: Summative-Naturalistic Evaluation – Qualitative Findings

This chapter describes the qualitative findings from semi-structured interviews with appropriately selected employees from SMEs, who as per the research methodology, are the users of the proposed Artifact. The main purpose of this analysis is to provide an answer to Research Question 4 (Dimension4) with a particular emphasis on the "User Acceptance" construction. The qualitative evidence collected sheds light on the human side of the story and the reasoning behind the quantitative data; thus, they confirm the attainment of the ultimate research goal: "positive user acceptance."

Thematic analysis of the interview transcripts has given the researchers insight into the behavioral and cognitive patterns of the participants that have been reinterpreted and discussed under the concepts of "Perceived Usefulness and Ease of Use," "Trust and Human Agency," and "Formative Feedback." The three broad themes resulted from the systematic coding of semi-structured interviews that followed the guide for the interviews in Appendix A. The interview form was created to draw out open-ended responses concerning daily workflow challenges, experiences with technology adoption, and expectations of automated solutions, thus making sure that the data included not only the explicitly stated issues but also the implicitly expressed attitudes toward the proposed artifact. The appendix also has the full codebook that links the interview questions with the corresponding themes and can be used as a record of the analysis process.

Perceived Usefulness and Ease of Use in the Technology Acceptance Model (TAM). Analysis of the data revealed that the users see the designed Artifact not just as a minor change, but as a "paradigm shift" in their work that most of the challenging and boring parts of their daily tasks have been taken out of their hands. This discovery is a direct empirical support for the "Perceived Usefulness" component of the Technology Acceptance Model (TAM). The worth of the Artifact for the users has both functional and emotional (alleviation of work-related stress) aspects. Supporting this, one of the users asserted: *"It's not just a speed increase; it takes out a part of my job that I really didn't like. I used to always have a long queue... that I would constantly look at. Now, I finish*

the entire backlog every day; I really feel a sense of relief." This positive change in the work experience has, therefore, become a strong factor for system acceptance.

Besides usefulness, the "Human-in-the-loop" workflow was also considered by the users as very natural because it corresponded to their mental models. The users were absolutely in favor of the "Review-Verify" process provided by the system rather than the manual "Create from scratch" process. The reason why the Artifact's design has been successful is that it has brought about less cognitive load and "context-switching"; in the usual method, the user had to be simultaneously a researcher, a writer, and a data entry operator, hence, a person performing multiple roles, while the new system has merged these roles into the single entity of a "Verifier" (see Appendix 3 for the operation sequence and user interface). Enumerating this facility, one of the participants said: *"With the old system, I had to open 10 browser tabs for each item... Now I just check what the app has gathered for me and simply click 'Confirm'. Maybe I correct one thing, and then I immediately submit the information."* These utterances serve as evidence for the "Perceived Ease of Use" construct in the TAM model.

Though as a fully autonomous system scenario, users showed little trust, they at the same time, expressed a high degree of trust and satisfaction in the AI-Assisted system. The user in this approach is an "Expert" and their "Tacit Knowledge" is acknowledged. One user's statement that sums up the importance of this issue is as follows: *"…Today it said a shirt with a Marimekko pattern was basically 'Marimekko,' but I know it is a counterfeit sample. I am the expert on this subject. But… it did 90% of the work for me. It's like a new intern, but one that learns instantly and doesn't get tired or complain."* These findings suggest that the "Human-in-the-loop" design is a strong point rather than a weakness, and thus a key feature that facilitates acceptance, which upgrades the user's role from just a simple operator to an "AI-Enabled Expert" while at the same time, their feeling of agency and control is maintained.

Moreover, the qualitative assessment had a "Formative" dimension as well, in which the users gave specific operational feedback for the upcoming cycles of the Design Science Research (DSR). Such feedback was essentially a clear roadmap for the next iterations of

the Artifact. For example, the slow image loading on the store's Wi-Fi network and the difficulty of changing categories via dropdown menus were problems pointed out. A user commenting on this matter said: *"It would be better if I could write the correction so that the AI understands it on its own."* The examination of this feedback resulted in the defining of steps towards rectification such as "Client-side compression" implementation and substitution of the conventional menus with a "Smart-search" feature in the forthcoming versions of the system. Moreover, the interview transcripts of three store employees are included as Appendix 3 to this research.

4.5 Summary of Results

This chapter has laid out in detail the entire results of the DSR project. The artifact, named “AI-MAS-on-Serverless,” has been efficiently engineered and executed (fourth DSR stage). The formative evaluation has been instrumental in enhancing the AI agent's reliability (fifth DSR stage, Phase 1). The summative evaluation has yielded strong quantitative and qualitative data (fifth DSR stage, Phase 2) that have been instrumental in confirming the artifact's validity concerning all the primary research objectives. Table 7 shows the final synthesis, and it is a direct mapping of this chapter's key findings with the research objectives and questions that were formulated in Chapter 1.

Table 7 Summary of Results Mapped to Research Objectives and Questions

Research Objective / Question	**Key Result / Finding**	**Location in Thesis**
RO1 (Design System): Design and develop a multi-agent AI system.	Achieved. Final "AI-MAS-on-Serverless" artifact demonstrated.	Section 4.1, Figure 8
Primary Objective 1: 80% time reduction.	Achieved (88.4%). Time per item reduced from 310s to 36s.	Section 4.3.1, Table 4

Primary Objective 2: 90% accuracy.	Achieved (94%). Aggregate accuracy on critical metadata fields.	Section 4.3.2, Table 5
Primary Objective 3: Positive user acceptance.	Achieved. Validated by qualitative thematic analysis.	Section 4.4
Dimension1 (Architecture): How can a MAS be designed...?	An event-driven, serverless architecture (AI-MAS-on-Serverless) is an effective, resilient, and accessible model for SMEs.	Section 4.1
Dimension2 (Performance): What is the system's accuracy and efficiency?	88.4% time reduction and 94% accuracy in a naturalistic setting.	Section 4.3
Dimension3 (Operational Impact): What is the quantified operational impact?	An 88% cost reduction per item (from €1.29 to €0.155), unlocking a previously unprofitable "long-tail" inventory.	Section 4.3.3, Table 6
Dimension4 (User Acceptance): How do employees perceive the system?	High acceptance. The "human-in-the-loop" design is essential for trust and augments, rather than replaces, human expertise.	Section 4.4.3
Dimension5 (Transferability): (To be answered in Ch. 5)	Findings suggest the *prompting pattern* (Section 4.2) and *human-in-the-loop* design (Section 4.4.3) are highly transferable.	N/A

5 Summary and conclusions

This chapter summarizes the thesis by combining the results presented in Chapter 4 and comparing them with the higher-level goals and research questions from Chapter 1. The way this chapter is set up is divided into four key parts: At first, a detailed review of the major findings is given, concentrating on an analytical answer to the five research questions that guided the study. Next, the effects of the results on the areas of "Industrial Management Practice" and "Academic Theory" are being discussed. After that, the acknowledgment of the study's limitations and the proposal of future research directions come. The chapter ends, in fact, with a recap of the total committal of this work under the "Design Science Research" (DSR) paradigm.

5.1 Summary of Findings

This DSR project effectively conceptualized, executed, and assessed a Multi-Agent AI system to solve the "scalability-sustainability paradox" issue in second-hand retail. The study offers definite, data-backed answers to the research questions introduced in Chapter 1. The findings are summarized in Table 8 to give a brief overview of the accomplishment of the research objectives.

Table 8 Summary of Research Questions, Objectives, and Key Findings

Research Question (RQ) & Objective (RO)	**Key Findings & Degree of Achievement**
Dimension1 (Architecture): How can a multi-agent AI system be designed for SME constraints? *(Linked to RO1)*	Achieved: "AI-MAS-on-Serverless" • Designed an event-driven architecture using Firebase and Gemini LLMs. • Key Mechanism: Orchestrator Agent triggering specialized cognitive agents (Vision, Text, OCR) via asynchronous cloud functions.

	• SME Fit: Zero-upfront cost serverless infrastructure solves the financial barrier.
Dimension2 (Performance): What are the system's accuracy and efficiency in a real-world environment? *(Linked to RO2)*	Achieved: Exceeded Targets • Efficiency: Processing time reduced by 88.4% (310s → 36s per item). • Accuracy: Aggregate metadata accuracy of 94%, surpassing the 90% target. • Constraint: Subjective "Condition" assessment had lower accuracy (86%), necessitating Human-in-the-Loop.
Dimension3 (Operational Impact): What are the operational impacts compared to manual practices? *(Linked to RO3)*	Achieved: Economic Viability • Cost Reduction: Digitization cost dropped from €1.29 to €0.155 per item. • Scalability: Digital processing capacity increased 8x with existing staff. • Result: The "long-tail" of low-value inventory is now profitable to digitize.
Dimension4 (User Acceptance): How do employees perceive the system? *(Linked to RO2)*	Achieved: High Acceptance via "Role Transformation" • Users accepted the system as a "reliable assistant" rather than a threat. • The workflow shifted from tedious data entry to expert "Quality Auditing," reducing cognitive load.
Dimension5 (Transferability): Are the design principles transferable to other SMEs? *(Linked to RO3)*	Achieved: Modular Design Principles • While specific accuracy varies by product type, the Prompt Constraint Pattern and Serverless Architecture are universally applicable to unstructured data tasks in resource-constrained SMEs.

This DSR project was initiated with the objective of designing, implementing, and evaluating a Multi-Agent Artificial Intelligence system to resolve the critical operational bottleneck of manual inventory digitization in SMEs operating within the second-hand retail sector. The analysis of the study's findings provides clear answers to the five research questions.

In response to Research Question 1 (Architecture), the study successfully designed and implemented an innovative architecture titled "AI-MAS-on-Serverless." Built upon a serverless infrastructure (Firebase) and Multimodal Large Language Models (Gemini), this architecture proved capable of fully automating the complex process of digitizing heterogeneous inventory. The technical and commercial feasibility of this design demonstrated that by utilizing an event-driven approach, triggered by image uploads—and employing an Orchestrator Agent to manage the workflow between cognitive and synchronization agents, fundamental challenges regarding technical accessibility in SME environments can be effectively overcome.

Regarding Research Question 2 (Performance), the quantitative evaluation of the system revealed achievements surpassing the initial objectives. The developed system succeeded in reducing the processing time per item by 88.4%, transforming a manual 310-second process into a "Human-in-the-loop" (HITL) workflow taking only 36 seconds. Simultaneously, the system's cumulative accuracy in extracting objective metadata (such as category, brand, and color) reached 94%, exceeding the 90% target, thereby confirming the high efficacy of the designed artifact.

Findings related to Research Question 3 (Operational Impact) indicate a profound transformation in the business's economic structure. The dramatic reduction in processing time translated to an 88% decrease in digitization costs, reducing the processing cost per item from €1.29 to €0.155. This achievement, by making the digitization of low-value (long-tail) goods profitable, directly removed scalability barriers and increased the SME's digital capacity by eightfold, providing a practical solution to the "Scalability-Sustainability" paradox.

In examining Research Question 4 (User Acceptance), qualitative analyses indicated high system acceptance among staff, rooted in the HITL design approach. Users perceived the system not as a replacement, but as an "intelligent and reliable assistant." By handling 94% of repetitive cognitive tasks, the system allowed staff to focus on the remaining 6% requiring human expertise (such as authentication). This constructive interaction compensated for the AI's relative weakness in assessing subjective "Condition" through human oversight, thereby fostering user trust.

Finally, in response to Research Question 5 (Transferability), the research demonstrated that while quantitative results are context-dependent, the fundamental "Design Principles" possess high transferability. Two key principles, the "AI-MAS-on-Serverless" architecture as a technical blueprint for low-cost implementation, and the "Prompt Constraint Pattern" for standardizing generative model outputs, were identified as generalizable solutions for other SMEs and sectors dealing with unstructured data.

5.2 Implications for Theory and Practice

This research findings provide various benefits to the management of the operation of circular economies, the understanding of AI adoption, and the practical strategies of SME managers. In order to make a clear distinction between the recorded data (Empirical), the theoretical models (Conceptual), and the feasible instructions (Practical), these consequences are outlined in Table 9.

Table 9 Synthesis of Empirical, Conceptual, and Practical Implications

Domain	**Contribution Area**	**Description & Impact**
Empirical *(Observed Evidence)*	Economic Validation of the "Long-Tail"	Impact: Quantitatively proved that reducing transaction costs to €0.155 effectively "unlocks" long-tail inventory. Significance: Empirically contradicts the assumption that high-variance, low-value goods cannot be profitably digitized without enterprise-scale resources.

	Performance Benchmarking	Impact: Established a concrete benchmark of 88.4% time reduction for retail tasks using Multimodal LLMs. Significance: Moves the academic discussion from theoretical potential to measured operational reality.
	Necessity of Human-in-the-Loop	Impact: Revealed a critical accuracy gap between objective fields (94%) and subjective fields (86%). Significance: Validates that human oversight is an operational requirement, not just a safety measure, for subjective valuation in second-hand markets.
Conceptual *(Theoretical Frameworks)*	"AI-MAS-on-Serverless" Design Theory	Impact: Proposed a validated architectural blueprint for SMEs. Significance: Theorizes that combining *Multi-Agent Systems* (complexity handling) with *Serverless Computing* (cost removal) is the optimal path for democratizing automation.
	The Prompt Constraint Pattern	Impact: Defined a pattern (Role-Playing + Schema Enforcement + Few-Shot) for Business Process Automation (BPA). Significance: demonstrable method to force non-deterministic GenAI models to output deterministic, transactional JSON data.
	FEDS Adaptation for Micro-Enterprises	Impact: Adapted the Framework for Evaluation in Design Science (FEDS) for resource-constrained environments. Significance: Provides a conceptual model for conducting rigorous "Naturalistic Evaluation" without large-scale R&D budgets.
Practical *(Managerial Action)*	Adoption of "Verifier" Workflows	Action: Redesign staff roles from "Data Entry" to "Quality Auditors." Benefit: Increases user trust and ensures data quality without requiring staff to have deep technical skills.
	Prioritizing Serverless Infrastructure	Action: Shift IT strategy from fixed-cost software licenses to pay-per-use serverless architectures. Benefit: Aligns operational costs directly with revenue generation, avoiding the "Scalability-Sustainability" paradox.

As far as the dimension of Practice and Management is concerned, the thesis offers an affordable and well-functioning plan for digital transformation of SMEs and the circular economy, which has been confirmed by practice. The outcomes disprove the general idea that only big companies can highly automate themselves. By an instance of a pay-as-you-go model and inexpensive APIs, the designed system lowers the entrance gates thus offering a real resolution to the problem of the necessity of technology versus lack of money. In this way, managers may decrease the firm’s running costs and even free up money that is lying dormant in the warehouse inventory thus putting into practice sustainable business models while competing in digital markets.

This thesis makes three significant contributions from the Theoretical and Academic point of view. Firstly, within the "Design Science Research" (DSR) area, the paper serves as a detailed example of using the FEDS framework in research, showing the way to characterize and verify quantitative goals in the actual setting. Secondly, in the field of "Information Systems" (IS) it suggests the new design theory that explains how the technology adoption in small and medium enterprises can be supported if they use the combination of Multi-Agent Systems (to handle complexity) and Serverless Computing (to lower the cost). Finally, the "Prompt Constraint Pattern" in "Business Process Automation" (BPA) is presented as a method of recasting raw data into dependable JSON outputs, thus making a considerable move to closing the automation gap for those processes which are flexible and non-standard in nature.

5.3 Limitations and Directions for Future Research

It is equally important to recognize the limitations of the study and the potential research avenues that arise from these limitations to ensure scientific rigor and also to define the scope of the findings.

The Limitations of the Study are mostly related to four main areas: Firstly, the "Generalizability" of the quantitative results since this study was a single case study, and exact numbers (like the 88.4%-time reduction) may be different in other situations. Secondly, the "Scope of the Artifact" that is still at the "Proof-of-Concept" stage and does not have production-level features such as multi-tenancy. Thirdly, the "Evaluation Timeframe" which did not allow the assessment of long-term economic and behavioral effects. Fourthly, "Technological Dependency" on the Google platform, which links system performance to the policies of this particular service provider. According to these limitations, Future Research Areas can be outlined as follows:

(1) *Replication and Generalizability:* Reproducing the DSR protocol in different retail sectors (e.g., antiques) or other industries (e.g., museum archiving) to verify the external validity of the design principles.

(2) *AaaS Platform Engineering:* Transforming the present artifact into a complete "Agent as a Service" (AaaS) platform, thus, scalability and data security issues must be contemplated for the research.

(3) *Longitudinal Studies:* Implementing prolonged studies (12 to 24 months) for obtaining accurate measures of Return on Investment (ROI) and changes in user behavior over time.

(4) *AI Ecosystem Expansion:* Employing specialized Computer Vision models for exact detection of physical defects and introducing new intelligent layers such as dynamic pricing, which in turn can double the system's value proposition.

5.4 Concluding Remarks

The main point of this thesis was to come up with a solution for a real operational problem: the inefficiency of manual digitization processes in the circular economy. By applying a strict DSR methodology, the research was able to produce the "AI-MAS-on-Server-

less" artifact which in fact quantitatively met the goals such as cutting time and increasing accuracy and also user trust and acceptance through a human-centric design were awarded.

As a matter of fact, this research is a demonstration of the intelligent use of modern cloud architectures and Generative AI to be able to change radically the traditional inventory management paradigms of SMEs. The design principles derived in this thesis open the way to a future in which advanced technologies are not a luxury but are accessible tools that ensure the sustainability and the circular economy's competitiveness.

References

Abbas, Q., Imran, M., & Sattar, A. (2025). From linear to circular: The impact of economic policies and technological innovations on greenhouse gas emissions in the Netherlands. *Carbon Balance and Management*, *20*(1), 11. https://doi.org/10.1186/s13021-025-00297-1

Acosta Llano, E., Hurmelinna-Laukkanen, P., & Haapanen, L. (2025). Blockchain for the circular economy, implications for public governance. *International Journal of Public Sector Management*, *38*(1), 30–52. https://doi.org/10.1108/IJPSM-12-2023-0365

Ali, A. A. A., Fayad, A. A. S., Alomair, A., & Al Naim, A. S. (2024). The Role of Digital Supply Chain on Inventory Management Effectiveness within Engineering Companies in Jordan. *Sustainability*, *16*(18), 8031. https://doi.org/10.3390/su16188031

Ameya Gokhale. (2025). Autonomous AI Agents in Online Retail: The Next Leap in Programmatic Media Buying. *International Journal of Scientific Research in Computer Science, Engineering and Information Technology*, *11*(2), 2713–2722. https://doi.org/10.32628/CSEIT25112732

Anay. (2024). How Has The Rise Of E-Commerce Platforms Affected Traditional Retail Markets And Consumer Shopping Behavior. *IOSR Journal of Business and Management*, *26*(10), 48–65. https://doi.org/10.9790/487X-2610134865

Appelgren, S. (2019). History as business: Changing dynamics of retailing in Gothenburg's second-hand market. *Business History*, *61*(1), 172–186. https://doi.org/10.1080/00076791.2018.1447563

Arroyabe, M. F., Arranz, C. F. A., Fernandez De Arroyabe, I., & Fernandez De Arroyabe, J. C. (2024). Analyzing AI adoption in European SMEs: A study of digital capabilities, innovation, and external environment. *Technology in Society*, *79*, 102733. https://doi.org/10.1016/j.techsoc.2024.102733

Balsalobre-Lorente, D., Shah, S. A. R., & Huseynova, R. (2024). Do circular economy, public-private Partnership and carbon policy manage the environmental stress? Developed countries' situation under the Prism of COP27. *Heliyon*, *10*(13), e33532. https://doi.org/10.1016/j.heliyon.2024.e33532

Barton, M., Budjac, R., Tanuska, P., Sladek, I., & Nemeth, M. (2024). Advancing Small and Medium-Sized Enterprise Manufacturing: Framework for IoT-Based Data Collection in Industry 4.0 Concept. *Electronics*, *13*(13), 2485. https://doi.org/10.3390/electronics13132485

Baruönü, F. Ö. (2025). Examining the motives affecting the demand for second-hand fashion products in the context of brand knowledge presence. *Journal of Product & Brand Management*, *34*(5), 707–719. https://doi.org/10.1108/JPBM-10-2023-4778

Brooks, A. (2025). The International Second-Hand Clothing Trade: Contributions to Sustainability and the Circular Economy. *Sustainability*, *17*(18), 8397. https://doi.org/10.3390/su17188397

Bus Econ J. (2024). E-commerce and its Disruption in Traditional Retail Markets. *Business and Economics Journal*, *15*(05), 45–58.

Chakraborti, T., Isahagian, V., Khalaf, R., Khazaeni, Y., Muthusamy, V., Rizk, Y., & Unuvar, M. (2020). From Robotic Process Automation to Intelligent Process Automation:

– Emerging Trends –. In A. Asatiani, J. M. García, N. Helander, A. Jiménez-Ramírez, A. Koschmider, J. Mendling, G. Meroni, & H. A. Reijers (Eds.), *Business Process Management: Blockchain and Robotic Process Automation Forum* (Vol. 393, pp. 215–228). Springer International Publishing. https://doi.org/10.1007/978-3-030-58779-6_15

Chanaka. (2023, January 14). Firebase cloud functions [Medium]. *Firebase Cloud Functions*.

Charnley, F., Knecht, F., Muenkel, H., Pletosu, D., Rickard, V., Sambonet, C., Schneider, M., & Zhang, C. (2022). Can Digital Technologies Increase Consumer Acceptance of Circular Business Models? The Case of Second Hand Fashion. *Sustainability*, *14*(8), 4589. https://doi.org/10.3390/su14084589

Chava, S., Oettl, A., Singh, M., & Zeng, L. (2024). Creative Destruction? Impact of E-Commerce on the Retail Sector. *Management Science*, *70*(4), 2168–2187. https://doi.org/10.1287/mnsc.2023.4795

Chavez, Z., Hauge, J. B., & Bellgran, M. (2022). Industry 4.0, transition or addition in SMEs? A systematic literature review on digitalization for deviation management. *The International Journal of Advanced Manufacturing Technology*, *119*(1–2), 57–76. https://doi.org/10.1007/s00170-021-08253-2

Chopra, S. (2019). *Supply chain management: Strategy, planning, and operation*. Harlow: Pearson Education. https://cir.nii.ac.jp/crid/1130282270219251072

Cohen, J. (1960). A Coefficient of Agreement for Nominal Scales. *Educational and Psychological Measurement*, *20*(1), 37–46. https://doi.org/10.1177/001316446002000104

Cooper, R. G. (2025). SMEs' use of AI for new product development: Adoption rates by application and readiness-to-adopt. *Industrial Marketing Management*, *126*, 159–167. https://doi.org/10.1016/j.indmarman.2025.01.016

Crisan, E. L., Chis, D. M., Bodea, E. E., & Buchmann, R. (2023). Mechanisms for robotic process automation implementation in organizations: A systematic literature review. *Journal of Advances in Management Research*, *20*(5), 920–946. https://doi.org/10.1108/JAMR-04-2023-0100

D'Adamo, I., Lupi, G., Morone, P., & Settembre-Blundo, D. (2022). Towards the circular economy in the fashion industry: The second-hand market as a best practice of sustainable responsibility for businesses and consumers. *Environmental Science and Pollution Research*, *29*(31), 46620–46633. https://doi.org/10.1007/s11356-022-19255-2

David Iyanuoluwa Ajiga, Ndubuisi Leonard Ndubuisi, Onyeka Franca Asuzu, Oluwaseyi Rita Owolabi, Tula Sunday Tubokirifuruar, & Rhoda Adura Adeleye. (2024). AI-DRIVEN PREDICTIVE ANALYTICS IN RETAIL: A REVIEW OF EMERGING TRENDS AND CUSTOMER ENGAGEMENT STRATEGIES. *International Journal of Management & Entrepreneurship Research*, *6*(2), 307–321. https://doi.org/10.51594/ijmer.v6i2.772

Dwivedi, A., & Paul, S. K. (2022). A framework for digital supply chains in the era of circular economy: Implications on environmental sustainability. *Business Strategy and the Environment*, *31*(4), 1249–1274. https://doi.org/10.1002/bse.2953

Ellen MacArthur Foundation. (2021). *Completing the picture: How the circular economy tackles climate change* (p. 68) [Report]. Ellen MacArthur Foundation. https://www.ellenmacarthurfoundation.org/completing-the-picture

Enshassi, M., Nathan, R. J., Soekmawati, & Ismail, H. (2025). Unveiling barriers and drivers of AI adoption for digital marketing in Malaysian SMEs. *Journal of Open Innovation: Technology, Market, and Complexity*, *11*(2), 100519. https://doi.org/10.1016/j.joitmc.2025.100519

Finnish Commerce Federation. (2023, September 21). *Finland is one of the world's leading second-hand markets*. Kauppa. https://kauppa.fi/en/uutishuone/2023/09/21/finland-is-one-of-the-worlds-leading-second-hand-markets/

Fisher, M. L., & Raman, A. (2010). The New Science of Retailing: How Analytics are Transforming the Supply Chain and Improving Performance. *Retail Merchandiser*, *50*(3), 6.

Fnu Imran Ahamed. (2025). Revolutionizing Retail: How Artificial Intelligence is Transforming the Customer Experience. *Journal of Computer Science and Technology Studies*, *7*(2), 357–367. https://doi.org/10.32996/jcsts.2025.7.2.37

Fuentes, C., & Hedegård, L. (2025). Recirculating products: Valuation practices and the socio-material making of second-hand products. *European Journal of Marketing*, *59*(13), 391–418. https://doi.org/10.1108/EJM-12-2022-0849

Gartner. (2025). Digitalization. In *Gartner IT Glossary*. Gartner, Inc. https://www.gartner.com/en/information-technology/glossary/digitalization

Gebauer, H., Fleisch, E., Lamprecht, C., & Wortmann, F. (2020). Growth paths for overcoming the digitalization paradox. *Business Horizons*, *63*(3), 313–323. https://doi.org/10.1016/j.bushor.2020.01.005

Generating content | Gemini API. (2025). Google AI for Developers. https://ai.google.dev/api/generate-content

George, Tegan. (2023, June 22). *Semi-Structured Interview | Definition, Guide & Examples*. Scribbr. https://www.scribbr.com/methodology/semi-structured-interview/

Greg Roughan. (2022, October 13). *What does ERP cost? An SME's guide* [Unleashed Software]. https://www.unleashedsoftware.com/blog/what-does-erp-cost-an-smes-guide/

Gu, W., Luo, J., Yu, X., Zhang, W., & Li, B. (2023). Dynamic decisions between sellers and consumers in online second-hand trading platforms: Evidence from C2C transactions. *Transportation Research Part E: Logistics and Transportation Review*, *177*, 103257. https://doi.org/10.1016/j.tre.2023.103257

Guiot, D., & Roux, D. (2010). A Second-hand Shoppers' Motivation Scale: Antecedents, Consequences, and Implications for Retailers. *Journal of Retailing*, *86*(4), 355–371. https://doi.org/10.1016/j.jretai.2010.08.002

He, K., Zhang, X., Ren, S., & Sun, J. (2016). Deep Residual Learning for Image Recognition. *2016 IEEE Conference on Computer Vision and Pattern Recognition (CVPR)*, 770–778. https://doi.org/10.1109/CVPR.2016.90

Hedegård, L. (2024). (Re)framing used goods: Marketing strategies in second-hand retail. *International Journal of Retail & Distribution Management*, *52*(13), 136–153. https://doi.org/10.1108/IJRDM-05-2023-0300

Hernández, V., Revilla, A., & Rodríguez, A. (2024). Digital data-driven technologies and the environmental sustainability of micro, small, and medium enterprises: Does size matter? *Business Strategy and the Environment*, *33*(6), 5563–5582. https://doi.org/10.1002/bse.3765

Hevner, A. R., March, S. T., Park, J., & Ram, S. (2004). Design science in information systems research. *MIS Q.*, *28*(1), 75–105.

Hultberg, E. (2025). Scaling circular business models: Strategic paths of second-hand fashion retail. *Journal of Fashion Marketing and Management: An International Journal*, *29*(2), 181–197. https://doi.org/10.1108/JFMM-10-2023-0260

Ifinedo, P. (2011). AN EMPIRICAL ANALYSIS OF FACTORS INFLUENCING INTERNET/E-BUSINESS TECHNOLOGIES ADOPTION BY SMES IN CANADA. *International Journal of Information Technology & Decision Making*, *10*(04), 731–766. https://doi.org/10.1142/S0219622011004543

Ishengoma, F., & John, E. (2025). Factors influencing the adoption of mobile-based AI services in Tanzanian manufacturing SMEs. *Vilakshan - XIMB Journal of Management*, *22*(2), 234–252. https://doi.org/10.1108/XJM-11-2023-0214

Jalil, M. F., Lynch, P., Marikan, D. A. B. A., & Isa, A. H. B. M. (2025). The influential role of artificial intelligence (AI) adoption in digital value creation for small and medium enterprises (SMEs): Does technological orientation mediate this relationship? *AI & SOCIETY*, *40*(3), 1875–1896. https://doi.org/10.1007/s00146-024-01969-1

Jiang, G., Chen, F., & Gu, M. (2025). Supply chain digitization and energy resilience: Evidence from China. *Energy Economics*, *144*, 108420. https://doi.org/10.1016/j.eneco.2025.108420

Jordan, P. W., Thomas, B., McClelland, I. L., & Weerdmeester, B. (Eds.). (1996). SUS: A "Quick and Dirty" Usability Scale. In *Usability Evaluation In Industry* (0 ed., pp. 207–212). CRC Press. https://doi.org/10.1201/9781498710411-35

Kallmuenzer, A., Mikhaylov, A., Chelaru, M., & Czakon, W. (2025). Adoption and performance outcome of digitalization in small and medium-sized enterprises. *Review of Managerial Science*, *19*(7), 2011–2038. https://doi.org/10.1007/s11846-024-00744-2

Karhunen, H. (2024). *Consumer Behavior of Young Finns Towards Second-Hand Clothing* [Thesis]. Bachelor's thesis, Turku University of Applied Sciences.

Khan, A. N., Mehmood, K., & Soomro, M. A. (2024). Knowledge Management-Based Artificial Intelligence (AI) Adoption in Construction SMEs: The Moderating Role of Knowledge Integration. *IEEE Transactions on Engineering Management*, *71*, 10874–10884. https://doi.org/10.1109/TEM.2024.3403981

Khan, U. A., Kauttonen, J., & Kudryavtsev, D. (2025). AI Adoption in Finnish SMEs: Key Findings from AI Consultancy at a European Digital Innovation Hub. *2025 IEEE 23rd World Symposium on Applied Machine Intelligence and Informatics (SAMI)*, 000465–000470. https://doi.org/10.1109/SAMI63904.2025.10883271

Kumar, D., Agrawal, S., Singh, R. K., & Singh, R. K. (2023). Coordination of circular supply chain for online recommerce platform in industry 4.0 environment: A game-theoretic approach. *Operations Management Research*, *16*(4), 2081–2103. https://doi.org/10.1007/s12063-023-00384-x

Kurniawan, T. A., Othman, M. H. D., Liang, X., Goh, H. H., Gikas, P., Kusworo, T. D., Anouzla, A., & Chew, K. W. (2023). Decarbonization in waste recycling industry using digitalization to promote net-zero emissions and its implications on sustainability. *Journal of Environmental Management*, *338*, 117765. https://doi.org/10.1016/j.jenvman.2023.117765

Larsen, K. R., Lukyanenko, R., Mueller, R. M., Storey, V. C., Parsons, J., VanderMeer, D., & Hovorka, D. S. (2025). *VALIDITY IN DESIGN SCIENCE*.

Linda Lisa Maria Turunen & Maike Gossen. (2024). From Preloved to Reloved: How Second-Hand Clothing Companies Facilitate the Transaction of Used Garments. *Journal of Sustainability Research*, *6*(1). https://doi.org/10.20900/jsr20240002

Liu, X., Xie, L., Wang, Y., Zou, J., Xiong, J., Ying, Z., & Vasilakos, A. V. (2021). Privacy and Security Issues in Deep Learning: A Survey. *IEEE Access*, *9*, 4566–4593. https://doi.org/10.1109/ACCESS.2020.3045078

Machado, M. A. D., Almeida, S. O. D., Bollick, L. C., & Bragagnolo, G. (2019). Second-hand fashion market: Consumer role in circular economy. *Journal of Fashion Marketing and Management: An International Journal*, *23*(3), 382–395. https://doi.org/10.1108/JFMM-07-2018-0099

Mak, M., & Heijungs, R. (2022). Environmental Externalities of Secondhand Markets—Based on a Dutch Auctioning Company. *Sustainability*, *14*(3), 1682. https://doi.org/10.3390/su14031682

montonio. (2025, August 25). *Shopify vs WooCommerce: Choosing the right platform* [Montonio]. https://www.montonio.com/blog/shopify-vs-woocommerce-a-guide-to-choosing-the-right-platform

Moreira, S., Mamede, H. S., & Santos, A. (2024). Business Process Automation in SMEs: A Systematic Literature Review. *IEEE Access*, *12*, 75832–75864. https://doi.org/10.1109/ACCESS.2024.3406548

Narang, R., & Tiwari, S. (2024). Role of Modern Technology in Unorganized Retail Sector. *Journal of the Knowledge Economy*, *16*(1), 1717–1744. https://doi.org/10.1007/s13132-024-01769-4

Nascimento, D. L. M., Alencastro, V., Quelhas, O. L. G., Caiado, R. G. G., Garza-Reyes, J. A., Rocha-Lona, L., & Tortorella, G. (2019). Exploring Industry 4.0 technologies to enable circular economy practices in a manufacturing context: A business model proposal. *Journal of Manufacturing Technology Management*, *30*(3), 607–627. https://doi.org/10.1108/JMTM-03-2018-0071

Neri, A., Cagno, E., Susur, E., Urueña, A., Nuur, C., Kumar, V., Franchi, S., & Sorrentino, C. (2025). The relationship between digital technologies and the circular economy: A systematic literature review and a research agenda. *R&D Management*, *55*(3), 617–713. https://doi.org/10.1111/radm.12715

Neri, A., Negri, M., Cagno, E., Franzò, S., Kumar, V., Lampertico, T., & Bassani, C. A. (2023). The role of digital technologies in supporting the implementation of circular

economy practices by industrial small and medium enterprises. *Business Strategy and the Environment*, *32*(7), 4693–4718. https://doi.org/10.1002/bse.3388

Padmavathy, C., Swapana, M., & Paul, J. (2019). Online second-hand shopping motivation – Conceptualization, scale development, and validation. *Journal of Retailing and Consumer Services*, *51*, 19–32. https://doi.org/10.1016/j.jretconser.2019.05.014

Panigrahi, R. R., Shrivastava, A. K., & Nudurupati, S. S. (2024). Impact of inventory management on SME performance: A systematic review. *International Journal of Productivity and Performance Management*, *73*(9), 2901–2925. https://doi.org/10.1108/IJPPM-08-2023-0428

Parente, R. C., Geleilate, J.-M. G., & Rong, K. (2018). The Sharing Economy Globalization Phenomenon: A Research Agenda. *Journal of International Management*, *24*(1), 52–64. https://doi.org/10.1016/j.intman.2017.10.001

Peffers, K., Tuunanen, T., Rothenberger, M. A., & Chatterjee, S. (2007). A Design Science Research Methodology for Information Systems Research. *Journal of Management Information Systems*, *24*(3), 45–77. https://doi.org/10.2753/MIS0742-1222240302

Piedra-Muñoz, L., García-Granero, E. M., Tarpani, R. R. Z., & Gallego-Schmid, A. (2025). Digital Technologies: Description, Classification, and Links to Circular Economy. *Business Strategy and the Environment*, *34*(6), 6612–6639. https://doi.org/10.1002/bse.4312

Prasetyani, D., Cahyadin, M., Indriawati, R. M., & Santosa, A. (2025). Does technology adoption matter for SMEs? A literature review. *Journal of Entrepreneurship and Public Policy*, *14*(2), 351–375. https://doi.org/10.1108/JEPP-09-2023-0090

Prat, N., Comyn-Wattiau, I., & Akoka, J. (n.d.). *ARTIFACT EVALUATION IN INFORMATION SYSTEMS DESIGN-SCIENCE RESEARCH – A HOLISTIC VIEW*.

Ren, S., He, K., Girshick, R., & Sun, J. (2017). Faster R-CNN: Towards Real-Time Object Detection with Region Proposal Networks. *IEEE Transactions on Pattern Analysis and Machine Intelligence*, *39*(6), 1137–1149. https://doi.org/10.1109/TPAMI.2016.2577031

Rusch, M., Schöggl, J., & Baumgartner, R. J. (2023). Application of digital technologies for sustainable product management in a circular economy: A review. *Business Strategy and the Environment*, *32*(3), 1159–1174. https://doi.org/10.1002/bse.3099

Russell, S. J., Norvig, P., Chang, M.-W., Devlin, J., Dragan, A., Forsyth, D., Goodfellow, I., Malik, J., Mansinghka, V., Pearl, J., & Wooldridge, M. (2022). *Artificial intelligence: A modern approach* (Fourth edition. Global edition). Pearson. https://tritonia.finna.fi/Record/tria.382013

Saarinen, E. (2025, September 19). The growth of second-hand trade has exploded to 1400 million euros in two years – Fast fashion and cheap goods threaten to clog second-hand channels. *Uusiouutiset*. https://uusiouutiset.fi/en/kiertokaupan-kasvu-on-rajahtanyt-kahdessa-vuodessa-1400-miljoonaan-euroon-pikamuoti-ja-halpakraasa-uhkaavat-tukkia-second-hand-kanavia/

Sándor, Á., & Gubán, Á. (2022). A multi-dimensional model to the digital maturity life-cycle for SMEs. *International Journal of Information Systems and Project Management*, *10*(3), 58–81. https://doi.org/10.12821/ijispm100303

Sasu-Boakye, Y., & Olsson, V. (2024). *He impact of consumer-to-consumer online platforms on the competitive strategies of traditional second-hand retail stores in Southern Sweden* [MBA thesis, Blekinge Institute of Technology]. https://www.diva-portal.org/smash/get/diva2:1923833/FULLTEXT01.pdf

Satish Krishnamurthy, Krishna Kishor Tirupati, Sandhyarani Ganipaneni, Er. Aman Shrivastav, Prof. (Dr) Sangeet Vashishtha, & Shalu Jain. (2024). Leveraging AI and Machine Learning to Optimize Retail Operations and Enhance. *Darpan International Research Analysis*, *12*(3), 1037–1069. https://doi.org/10.36676/dira.v12.i3.140

Shapiro, S. S., & Wilk, M. B. (1965). An Analysis of Variance Test for Normality (Complete Samples). *Biometrika*, *52*(3/4), 591. https://doi.org/10.2307/2333709

Silver, E. A., Pyke, D. F., & Thomas, D. J. (2021). *Inventory and production management in supply chains* (Fourth edition, first issued in paperback). CRC Press, Taylor & Francis Group.

Suchek, N., Ferreira, J. J. M., & Fernandes, P. O. (2024). Industry 4.0 and global value chains: What implications for circular economy in SME? *Management Decision*, *62*(9), 2915–2936. https://doi.org/10.1108/MD-11-2022-1541

Team, G., Anil, R., Borgeaud, S., Alayrac, J.-B., Yu, J., Soricut, R., Schalkwyk, J., Dai, A. M., Hauth, A., Millican, K., Silver, D., Johnson, M., Antonoglou, I., Schrittwieser, J.,

Glaese, A., Chen, J., Pitler, E., Lillicrap, T., Lazaridou, A., … Vinyals, O. (2025). *Gemini: A Family of Highly Capable Multimodal Models* (No. arXiv:2312.11805). arXiv. https://doi.org/10.48550/arXiv.2312.11805

Tiwari, M. K., Bidanda, B., Geunes, J., Fernandes, K., & Dolgui, A. (2024). Supply chain digitisation and management. *International Journal of Production Research*, *62*(8), 2918–2926. https://doi.org/10.1080/00207543.2024.2316476

Tritto, N., Dias, J. G., & Bassi, F. (2024). SMEs Circular Economy Practices in the European Union: Multilevel Implications for Sustainability. *Social Indicators Research*, *175*(3), 965–988. https://doi.org/10.1007/s11205-023-03191-w

Trivedi, B. (2025). Retail Cybersecurity in the Agentic Age: Securing Autonomous Shopping Agents in E-Commerce. *European Modern Studies Journal*, *9*(4), 537–544. https://doi.org/10.59573/emsj.9(4).2025.52

Tung-Hsiang Chou, You-Sheng Chen, Chung-Wei Pan, & Hung-Hsuan Chang. (2024). A Smart Scale for Efficient Inventory Management Based on Design Science Research Principles. *Contemporary Economics*, *18*(2), 153–170. Business Source Ultimate.

Turunen, L. L. M., & Leipämaa-Leskinen, H. (2015). Pre-loved luxury: Identifying the meanings of second-hand luxury possessions. *Journal of Product & Brand Management*, *24*(1), 57–65. https://doi.org/10.1108/JPBM-05-2014-0603

Ulrich, P., & Frank, V. (2021). Relevance and Adoption of AI technologies in German SMEs – Results from Survey-Based Research. *Procedia Computer Science*, *192*, 2152–2159. https://doi.org/10.1016/j.procs.2021.08.228

Van Der Aalst, W. M. P., Bichler, M., & Heinzl, A. (2018). Robotic Process Automation. *Business & Information Systems Engineering*, *60*(4), 269–272. https://doi.org/10.1007/s12599-018-0542-4

Venable, J., Pries-Heje, J., & Baskerville, R. (2016). FEDS: A Framework for Evaluation in Design Science Research. *European Journal of Information Systems*, *25*(1), 77–89. https://doi.org/10.1057/ejis.2014.36

Verhoef, P. C., Neslin, S. A., & Vroomen, B. (2007). Multichannel customer management: Understanding the research-shopper phenomenon. *International Journal of Research in Marketing*, *24*(2), 129–148. https://doi.org/10.1016/j.ijresmar.2006.11.002

Wooldridge, M. J. (2012). *An introduction to multiagent systems* (2. ed., repr). Wiley.

Xia, Y., Narayanamoorthy, S., Zhou, Z., & Mabry, J. (2024). *Simulation-Based Benchmarking of Reinforcement Learning Agents for Personalized Retail Promotions*. https://doi.org/10.48550/arxiv.2405.10469

Yosephine, V. S., Batara, M., & Setiawati, M. (2025). Scalable and Affordable IoT-based Inventory Control with Real-Time Monitoring for Small and Medium Enterprises. *Jurnal Teknik Industri: Jurnal Keilmuan Dan Aplikasi Teknik Industri*, *27*(1), 121–136. https://doi.org/10.9744/jti.27.1.121-136

Yrjölä, M., Hokkanen, H., & Saarijärvi, H. (2021a). A typology of second-hand business models. *Journal of Marketing Management*, *37*(7–8), 761–791. https://doi.org/10.1080/0267257X.2021.1880465

Yrjölä, M., Hokkanen, H., & Saarijärvi, H. (2021b). A typology of second-hand business models. *Journal of Marketing Management*, *37*(7–8), 761–791. https://doi.org/10.1080/0267257X.2021.1880465

Appendices

Appendix 1. Complete Data Schema Specifications

Firestore Product Document Schema:

```
{
  "productData": {
    "title": "Vintage Leather Jacket, Brown, Size M",
    "category": "Fashion & Accessories > Clothing > Outer-
wear > Jackets",
    "description": "Classic brown leather jacket featur-
ing...",
    "price": "45",
    "location": "Display Case 3",
    "status": "Second Hand",
    "attributes": {
      "Size": "M",
      "Material": "Genuine Leather",
      "Color": "Brown",
      "Brand": "Unknown",
      "Condition": "Good"
    },
    "tags": ["vintage", "leather", "jacket"]
  },
  "imageUrls": ["gs://..."],
  "Item Code": "SKU-2025-0847",
  "Quantity": 1,
  "Store": "Helsinki Main Store",
  "savedAt": "2025-01-15T10:30:00Z"
}
```

Appendix 2. Interview Protocol and Evaluation Instruments

System Usability Scale (SUS) Questionnaire

Instructions: Rate agreement on 1-5 scale (1=Strongly Disagree, 5=Strongly Agree)

#	Statement	Rating
1	I think that I would like to use this system frequently	☐ ☐ ☐ ☐ ☐
2	I found the system unnecessarily complex	☐ ☐ ☐ ☐ ☐
3	I thought the system was easy to use	☐ ☐ ☐ ☐ ☐
4	I think that I would need the support of a technical person to use this system	☐ ☐ ☐ ☐ ☐
5	I found the various functions in this system were well integrated	☐ ☐ ☐ ☐ ☐
6	I thought there was too much inconsistency in this system	☐ ☐ ☐ ☐ ☐
7	I would imagine that most people would learn to use this system very quickly	☐ ☐ ☐ ☐ ☐
8	I found the system very cumbersome to use	☐ ☐ ☐ ☐ ☐
9	I felt very confident using the system	☐ ☐ ☐ ☐ ☐
10	I needed to learn a lot of things before I could get going with this system	☐ ☐ ☐ ☐ ☐

Appendix 3. Full Interview Transcripts (Qualitative Evaluation)

Study Phase: Summative-Naturalistic Evaluation (Phase 2)

Method: Semi-Structured Interviews & System Usability Scale (SUS) Administration

Participants: N=3 (1 Store Manager, 2 Inventory Staff)

Duration: Approx. 35-40 minutes per interview

Language: English (Transcribed)

Context: Evaluation of the "AI-MAS-on-Serverless" (i-Stock) system adoption within a Finnish second-hand retail environment.

Interview Transcript: Participant 1 (P1)

Role: Store Manager / Senior Valuator

Date: November 28, 2025

Location: Back-office / Processing Area

Interviewer: Thank you for sitting down with me, I know it's a busy time. I'd like to start broadly. How would you describe your overall experience moving from the manual process to using the AI-assisted system over the last two weeks?

Participant 1: [Exhales] Well, it has been... a significant change. Quite dramatic, actually. Honestly, at first, I was very skeptical. You know how it is—we have tried different software before, inventory apps, barcode scanners... and usually, they just add more steps to the process. They make promises but end up slowing us down. So when we started this, I thought, "Here we go again." But this was different.

Interviewer: Different in what way?

Participant 1: It didn't feel like I was fighting the computer. It felt less like data entry and more like... supervising. Or auditing, maybe?

Interviewer: Can you elaborate on that? How did your daily role change specifically?

Participant 1: Well, usually, if I'm doing the intake, my eyes are tired by noon. I'm typing descriptions, measuring items, checking brand names on Google to see if "Gant" is spelled with one T or two... it's tedious. I'm acting like a secretary for the products. With this system, I felt like my expertise was being used better. I wasn't wasting time figuring out if a shirt is blue or navy or looking up material codes; the AI does all that heavy lifting. I was focusing on the price and the authenticity—the things that actually bring value to the store.

Interviewer: That's a key distinction. Speaking of authenticity and trust, that's often a barrier with AI. How much did you trust the data the AI agents were generating?

Participant 1: That is an interesting point. In the beginning—maybe the first two days—I checked every single field. I didn't trust it at all. I was looking for mistakes. But after a few days, I realized the factual stuff—brand, color, material, the tags—was

almost always right. Surprisingly accurate. However, [pauses] you still need a human there. It's not magic.

Interviewer: Could you give me a specific example of why the human is still needed? Where did it struggle?

Participant 1: Yes, definitely. For example, today it said a shirt with a Marimekko pattern was basically 'Marimekko,' but I know it is a counterfeit sample. The print was slightly off, the fabric quality wasn't right. The AI sees the pattern and gets excited, says "Aha, Marimekko!" I am the expert on this subject. I can touch the fabric and know it's a fake. But… it did 90% of the work for me. It got the color, the style, the size, the category right. I just had to change the brand field and lower the price. It's like a new intern, but one that learns instantly and doesn't get tired or complain.

Interviewer: That is a great analogy. So, you see it effectively as a support tool rather than a replacement?

Participant 1: Absolutely. I don't see it taking my job. It doesn't know the history of a vintage item or how to spot a fake just by the fabric feel, or the sentimental value of certain items. But it handles the boring work. It lets me focus on being the expert, which is what I enjoy. And frankly, it lets us list items we wouldn't have bothered with before because it was too much effort for a 5-euro shirt. Now? It's easy.

System Usability Scale (SUS) Assessment - P1

Interviewer: To wrap up, I need to ask you 10 standard questions to rate the system's usability. Please rate each statement from 1 (Strongly Disagree) to 5 (Strongly Agree) based on your experience.

Interviewer: 1. I think that I would like to use this system frequently.

Participant 1: 5. Definitely. Going back to the manual way now would feel like a punishment.

Interviewer: 2. I found the system unnecessarily complex.

Participant 1: 1. Not at all. It's actually simpler than our old Excel sheets because the interface is so clean.

Interviewer: 3. I thought the system was easy to use.

Participant 1: 5. Very intuitive. The flow is logical.

Interviewer: 4. I think that I would need the support of a technical person to use this system.

Participant 1: 2. Maybe just for the initial login or if the Wi-Fi drops, but for the actual work? No. I can handle it myself.

Interviewer: 5. I found the various functions in this system were well integrated.

Participant 1: 5. Yes, the way the camera connects to the database instantly is seamless.

Interviewer: 6. I thought there was too much inconsistency in this system.

Participant 1: 2. It's mostly consistent. The only inconsistency is the AI's judgment on "Condition"—sometimes it says "Good" when I think "Fair"—but the system itself is stable.

Interviewer: 7. I would imagine that most people would learn to use this system very quickly.

Participant 1: 5. I think so. If I can teach the Saturday intern in 10 minutes, anyone can learn it.
Interviewer: 8. I found the system very cumbersome to use.
Participant 1: 1. "Cumbersome" is the word I'd use for the old way. This is the opposite.
Interviewer: 9. I felt very confident using the system.
Participant 1: 4. I am confident, but I still feel the need to audit the "Brand" field carefully, like I mentioned with the fake Marimekko. So, a solid 4.
Interviewer: 10. I needed to learn a lot of things before I could get going with this system.
Participant 1: 1. No, it's mostly just "Click and Verify." Not much to learn.

Interview Transcript: Participant 2 (P2)

Role: Inventory Staff (Focus on Sorting & Listing)

Date: November 28, 2025

Location: Processing Area

Interviewer: Let's talk about your daily workflow. Before this pilot, how did you manage the incoming donations?
Participant 2: Oh, it was stressful. [Laughs nervously] Chaotic, really. We get bags and bags of clothes every day. Some days, we couldn't even touch the new arrivals because we were still processing items from three days ago. The pile just kept growing in the corner. It stares at you, you know? You feel like you're never catching up.
Interviewer: That sounds overwhelming. And how did the new system affect that backlog over these two weeks?
Participant 2: It's hard to explain the feeling, but... it's not just a speed increase; it takes out a part of my job that I really didn't like. I used to always have a long queue... that I would constantly look at. I'd count them, thinking, "Okay, 50 more to go, that's 4 hours of typing." Now, I finish the entire backlog every day; I really feel a sense of relief. Yesterday, we actually ran out of things to list by 2 PM. That never happens.
Interviewer: That sounds like a major improvement in job satisfaction. What specifically made it faster for you? Was it one specific feature?
Participant 2: The photography part is easier because I don't have to worry about the background anymore; the AI fixes it, removes the messy room behind the product. That's nice. But mostly, it's the typing. I am not a fast typer, and my English spelling isn't perfect. Writing descriptions for 50 items used to take me all day. I'd get stuck thinking, "How do I describe this collar?" Now, I just take the picture, wait a few seconds, and the description is there. It uses fancy words I wouldn't have thought of, like "asymmetrical hem" or whatever.
Interviewer: [Laughs] So it improves the quality of the listings too?
Participant 2: Yes, definitely. The listings look more professional.
Interviewer: Did you find the system easy to learn?

Participant 2: Very easy. I am not very technical. I use my phone for social media, Instagram, things like that, but I am not good with complex computer programs or Excel. This was simple. Just upload, check, and save. It felt like an app I would use at home. I didn't need to ask for help after the first hour. It's very... straightforward.

System Usability Scale (SUS) Assessment - P2

Interviewer: Now, I'd like to get your rating on the system's usability. Please answer with a number from 1 (Strongly Disagree) to 5 (Strongly Agree).
Interviewer: 1. I think that I would like to use this system frequently.
Participant 2: 5. Please don't take it away! [Laughs] It makes my day so much shorter.
Interviewer: 2. I found the system unnecessarily complex.
Participant 2: 1. No, it has very few buttons. It's hard to get lost.
Interviewer: 3. I thought the system was easy to use.
Participant 2: 5. Like I said, very straightforward.
Interviewer: 4. I think that I would need the support of a technical person to use this system.
Participant 2: 1. I haven't needed to ask for help since the first morning training.
Interviewer: 5. I found the various functions in this system were well integrated.
Participant 2: 5. Everything works together. The camera, the text, the saving.
Interviewer: 6. I thought there was too much inconsistency in this system.
Participant 2: 1. I haven't noticed any. It works the same way every time.
Interviewer: 7. I would imagine that most people would learn to use this system very quickly.
Participant 2: 5. Even my mom could use this, and she hates computers.
Interviewer: 8. I found the system very cumbersome to use.
Participant 2: 1. Not at all. It's light and fast on the iPad.
Interviewer: 9. I felt very confident using the system.
Participant 2: 5. I feel good using it because I can see the result immediately.
Interviewer: 10. I needed to learn a lot of things before I could get going with this system.
Participant 2: 1. You just showed me the "Add Item" button, and that was it.

Interview Transcript: Participant 3 (P3)

Role: Inventory Staff (Part-time / Digital Focus)

Date: November 29, 2025

Location: Processing Area

Interviewer: You have experience listing items on online marketplaces manually before this pilot. How does the i-Stock workflow compare to the old way?
Participant 3: It is night and day. Completely different. With the old system, I had to open 10 browser tabs for each item—one for the pricing research, one for Google Translate, one for the store admin panel, maybe one for image editing... It was messy.

It was mentally exhausting switching contexts all the time, copy-pasting, alt-tabbing. You lose track of where you are. Now I just check what the app has gathered for me and simply click 'Confirm'. Maybe I correct one thing, and then I immediately submit the information. It's all in one view.

Interviewer: So, the "single-screen" dashboard approach helped with the workflow?

Participant 3: Yes, definitely. The cognitive load is much lower. I don't feel "fried" at the end of the shift. I can just get into a flow. Click, review, publish. Click, review, publish. It's almost satisfying.

Interviewer: We are also looking for ways to improve the system for the next iteration. Was there anything that frustrated you or could be designed better? Be honest.

Participant 3: Generally, it was great, really. But there were small things. For instance, when the AI gets the category slightly wrong—like calling a "Cardigan" a "Jacket"—I have to use the dropdown menu to find the right category manually. The menu is huge, like 150 options nested inside each other. Finding "Women > Tops > Knits > Cardigans" takes time.

Interviewer: That makes sense. How would you prefer to handle that correction?

Participant 3: It would be better if I could write the correction so that the AI understands it on its own. Like, if I could just type "change to Cardigan" or even speak to it, instead of scrolling through a long list. Just a quick command.

Interviewer: That's a very good idea, natural language correction. Also, I noticed some delays on Tuesday in the logs. Did that affect you?

Participant 3: A little bit. Our store Wi-Fi isn't the best in the back corner, the walls are thick. When the images were uploading, sometimes it took a while, maybe 10 seconds for the spinner to stop. If the system could compress the images on the phone before sending them, that might help. But honestly, compared to doing it manually—which takes 15 minutes—waiting 10 seconds is nothing. But yes, faster would be better.

System Usability Scale (SUS) Assessment - P3

Interviewer: Finally, let's do the quick SUS rating. 1 (Strongly Disagree) to 5 (Strongly Agree).

Interviewer: 1. I think that I would like to use this system frequently.

Participant 3: 5. It's the only way to scale up our online sales, so yes.

Interviewer: 2. I found the system unnecessarily complex.

Participant 3: 2. Mostly a 1, but I'll give it a 2 because of those nested dropdown menus. That part feels a bit clunky compared to the rest of the AI features.

Interviewer: 3. I thought the system was easy to use.

Participant 3: 4. Generally easy, minus the category correction part.

Interviewer: 4. I think that I would need the support of a technical person to use this system.

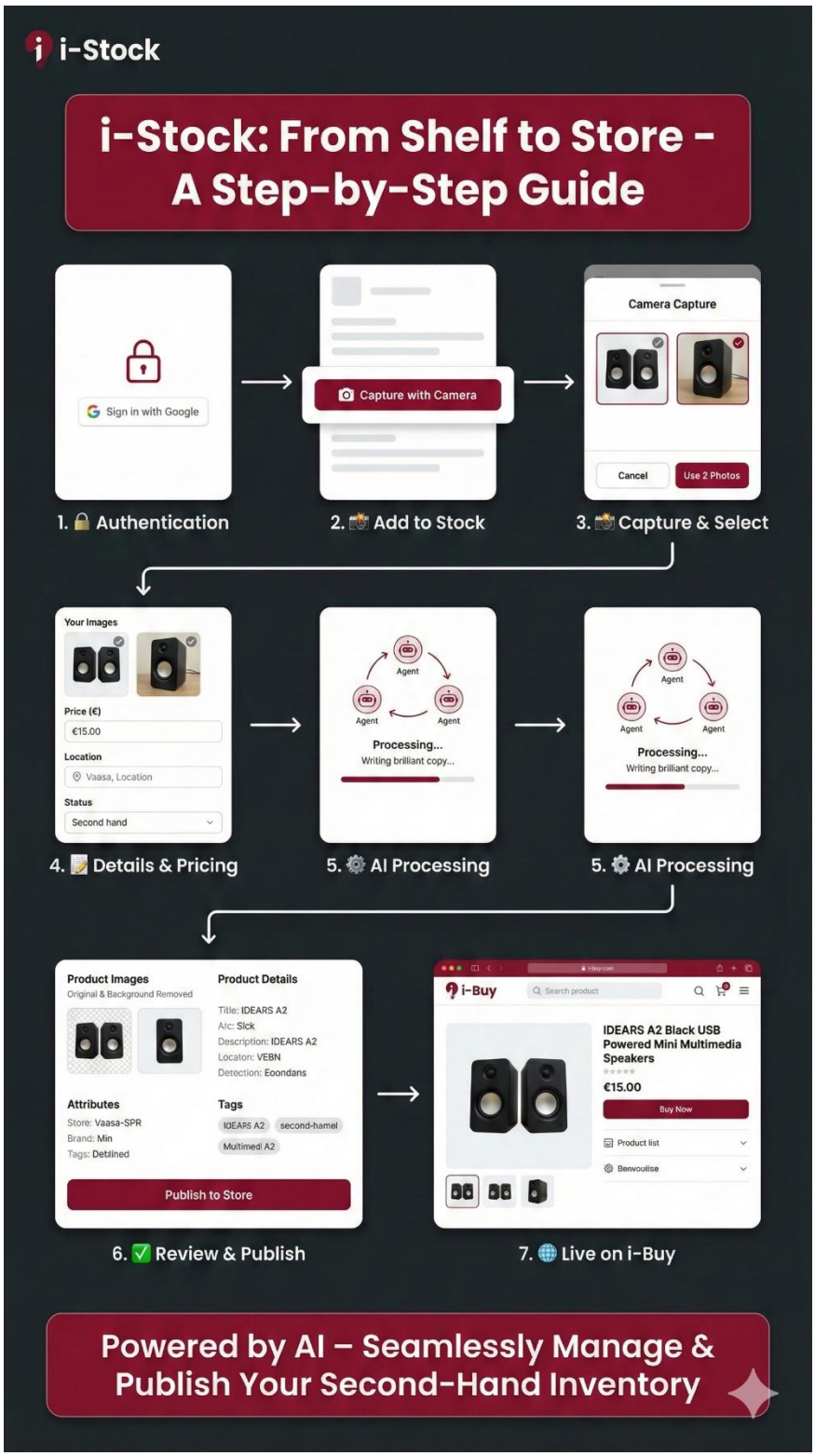
Participant 3: 1. No, I can troubleshoot basic issues myself.

Interviewer: 5. I found the various functions in this system were well integrated.

Participant 3: 4. The integration is good, though I wish the "Edit" function was a bit smarter, as I mentioned.

Interviewer: 6. I thought there was too much inconsistency in this system.
Participant 3: 1. It's very consistent.
Interviewer: 7. I would imagine that most people would learn to use this system very quickly.
Participant 3: 5. Yes, the learning curve is practically flat.
Interviewer: 8. I found the system very cumbersome to use.
Participant 3: 2. Only when the Wi-Fi is slow and the spinner hangs, or when I have to scroll through categories. Otherwise, it's smooth.
Interviewer: 9. I felt very confident using the system.
Participant 3: 5. I trust the process.
Interviewer: 10. I needed to learn a lot of things before I could get going with this system.
Participant 3: 1. Not really. It's very self-explanatory.
Interviewer: Thank you. That completes the interview.

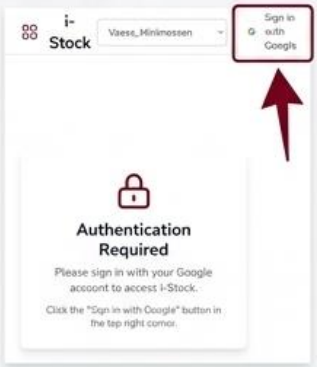
Appendix 4. A Step-by-Step User Interaction Guide for i-Stock: A Visual Documentation Approach



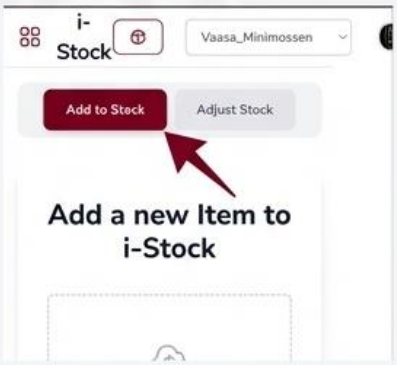
Appendix 5. UI Screens of the Developed Prototype

i-Stock Application Manual: Adding & Publishing to Stock

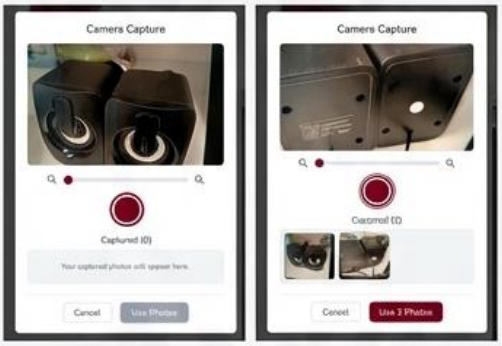
1. Login & Access



2. Add to Stock Path

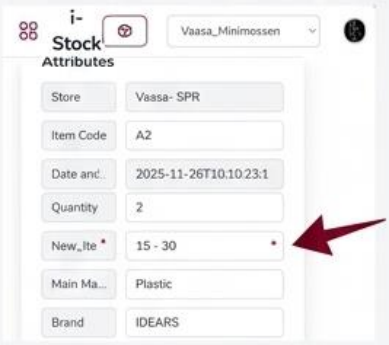


3. Capture Product Images



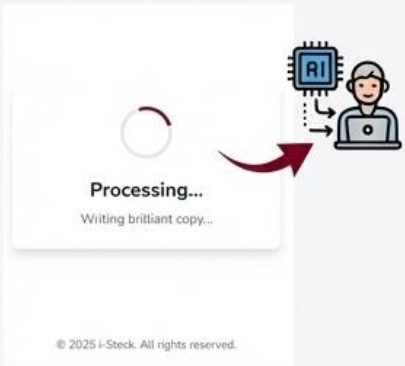
Take multiple photos of the object.

4. Add Product Details (Manual Form)

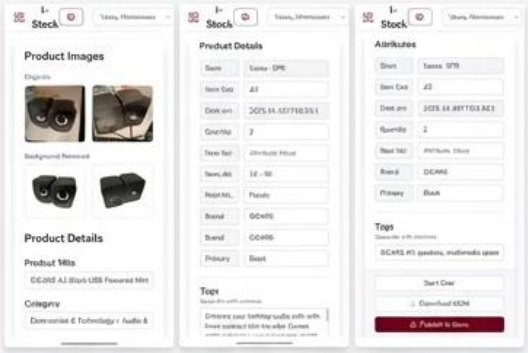


Price is Mandatory. Other fields are optional.

5. AI-Agent Processing

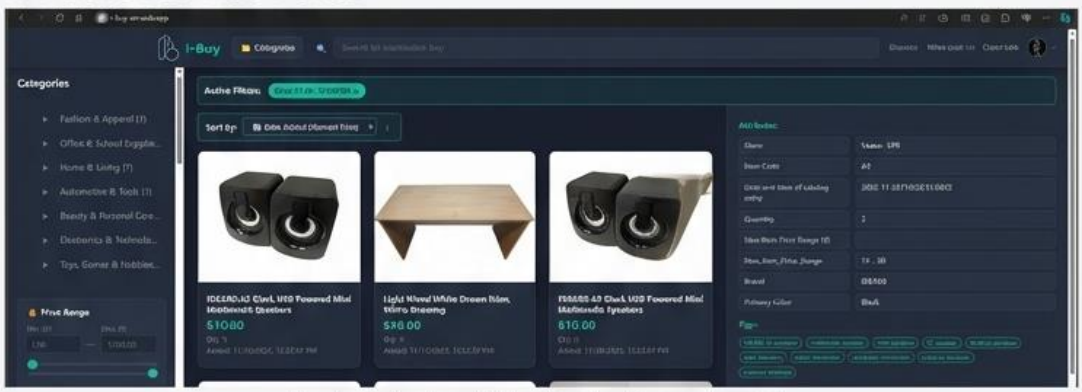


6. Pre-Publish Catalog Review



Review and edit AI-generated information.

7. Publish to Web Portal



Final catalog is published to the client web portal.