

Master's Programme in ICT Innovation - EIT Digital Masters School

AI Startup Website Optimization Through Canonical Action Research and Continuous Experimentation: An Iterative UX Design Study

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Title AI Startup Website Optimization Through Canonical Action Research and Continuous Experimentation: An Iterative UX Design Study

Degree programme ICT Innovation - EIT Digital Masters School

Major Human-Computer Interaction and Design

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Collaborative partner LEVELS

Date 28 September 2025

Number of pages 66+4

Language English

Abstract

Early-stage AI startups face critical challenges in optimizing their digital presence for lead generation while operating under severe resource constraints. Traditional website optimization approaches often fail in complex technical service domains where abstract capabilities must be communicated to diverse audiences. This thesis investigates how the integration of Canonical Action Research (CAR) methodology with Continuous Experimentation (CE) principles can enable effective website optimization in resource-constrained AI startup environments. The research addresses three key questions: how CAR-CE integration enables systematic website optimization, which design elements demonstrate strongest conversion impact, and how integrated digital marketing influences lead generation effectiveness. Using a mixed-methods approach, the study employed two iterative CAR cycles spanning three months within an Italian AI consulting startup, combining comprehensive web analytics through PostHog with qualitative user interviews and systematic hypothesis testing. Results revealed a critical conversion hierarchy where semantic clarity and information architecture significantly outweigh visual design elements in driving qualified leads. Key findings challenge conventional startup optimization approaches by establishing that contemporary UI/UX design improvements, while achieving strong engagement metrics, cannot overcome fundamental communication barriers in complex technical domains. Qualitative analysis identified four critical conversion barriers: ambiguity in core offering, technical jargon alienating users, flawed information hierarchy, and universal demand for tangible demonstrations over abstract capability descriptions. The research demonstrates that social media marketing functions primarily as brand awareness amplification rather than direct conversion, with offline-to-online integration achieving the strongest measurable attribution effects. Practically, the research provides actionable guidance for early-stage technical startups, emphasizing message clarity and user comprehension optimization before aesthetic improvements, fundamentally reorienting resource allocation strategies for sustainable growth through improved digital presence.

Keywords Canonical Action Research, Continuous Experimentation, Website Optimization, AI Startup, User Experience Design, Digital Marketing

Preface

I want to thank Professor Fabian Fagerholm, Professor Mariet Theune, MSc. Vihtori Mäntylä, and MSc. Filippo Calìò for their guidance.

I also want to thank my close friends and my family for supporting me during these two years.

Otaniemi, 28 September 2025

Gianluca Romeo

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1 Introduction

Early-stage startups face the dual challenge of rapid growth and limited resources [1]. The crowded Internet landscape necessitates a strong online presence to stand out among competitors. A measure of online visibility can help firms assess and improve their position relative to competitors, which is vital for client acquisition [2]. Traditional outbound marketing methods like cold-calling, email blasts, and direct mail are becoming less effective due to advancements in technology that help people block these interruptions (e.g., Caller ID, spam protection) [3]. Therefore, startups that rely heavily on outbound strategies, such as cold emailing, overlook the potential of their websites to generate organic leads.

Continuous Experimentation (CE) emerges as a particularly valuable methodology for resource-constrained startups seeking to optimize their digital presence systematically. CE is defined as a systematic, hypothesis-driven process for improving digital products through rapid cycles of testing and validation [4]. For early-stage companies, CE offers a structured approach to make evidence-based decisions while minimizing resource waste on ineffective interventions. Rather than implementing large-scale changes based on assumptions, CE enables startups to test specific hypotheses about user behavior, website elements, and marketing strategies through controlled experiments.

In websites, qualified leads are potential customers who have demonstrated genuine interest and meet specific criteria indicating purchasing intent. To enhance website engagement and convert visitors into qualified leads in early-stage startups, several evidence-based strategies can be employed. These strategies focus on improving website design and user experience, understanding user behaviors, and integrating social media campaigns to increase traffic.

User Experience (UX) and User Interface (UI) design are critical factors that significantly influence various website metrics, including user engagement, satisfaction, and overall usability [5]. Key elements such as intuitive navigation, appealing visuals, and performance optimization contribute to a seamless user journey, thereby increasing the likelihood of visitor-to-lead conversion.

Web analytics complement these strategies by providing insights into user behavior, preferences, and interaction patterns. By analyzing metrics such as bounce rates, click-through rates, and session durations, startups can identify areas for improvement and customize their websites to align with user expectations [6]. This data-driven approach ensures that design and content decisions are grounded in empirical evidence, enhancing the website's overall effectiveness.

In digital marketing, platforms like LinkedIn are instrumental for B2B startups in generating leads [7]. To effectively increase visibility and attract potential clients, integrating profile optimization, content marketing, and targeted outreach with website optimization is essential.

1.1 Research Questions

This thesis explores how UI/UX design improvements, systematic analytics implementation, and integrated social media marketing can enhance website performance for an early-stage AI startup.

The research employs Canonical Action Research (CAR) as its primary methodological framework. CAR is an iterative methodology that combines systematic organizational problem-solving with academic rigor through cyclical processes of design, testing, and analysis [8]. This framework is particularly suited to startup environments as it enables both practical organizational improvement and theoretical knowledge contribution through structured intervention cycles.

The CAR approach is enhanced through the integration of CE principles, creating a robust methodology for evidence-based website optimization. This combined framework enables the systematic investigation of the following research questions:

- **RQ1:** How can the application of Canonical Action Research methodology combined with Continuous Experimentation principles enable effective website optimization in resource-constrained AI startup environments?
- **RQ2:** Which design elements and content strategies, when evaluated through Continuous Experimentation principles, demonstrate the strongest measurable impact on lead qualification and conversion rates in resource-constrained AI startup environments?
- **RQ3:** How does integrated digital marketing strategy, particularly social media engagement combined with website analytics, influence traffic attribution and lead generation effectiveness in resource-constrained AI startup environments?

Through this investigation, the thesis will contribute to the academic discourse on startup growth strategies and provide practical insights for early-stage companies aiming to optimize their digital presence.

1.2 Project context

The project takes place within an early-stage AI-based software consulting startup whose primary challenge is the underperformance of its website in generating inbound leads. Current client acquisition relies heavily on outbound cold emailing, a practice that may not scale efficiently as the company grows. Improving website-led conversion is considered both a strategic priority and a practical experiment in applying data-driven methodologies to business development. By embedding Continuous Experimentation (CE) cycles within a Canonical Action Research (CAR) framework, the project aims to identify and test modifications to website elements, including copy, visuals, navigation, and forms, based on real user data and organizational objectives. Iterative interventions will focus on high-impact, low-cost changes, aligned with best practices in UX and analytics-driven decision making. The dual goals are to deliver actionable business outcomes (increased lead generation) and to contribute to academic knowledge on CAR and CE integration in early-stage startups.

1.3 Structure of the Thesis

The rest of this thesis is structured as follows.

In Chapter 2, existing literature on user experience design, continuous experimentation, web analytics, and digital marketing is reviewed to establish the theoretical foundation for the study.

Chapter 3 presents the research methods, detailing the canonical action research framework, data collection methods, and evaluation approaches employed throughout the iterative cycles.

Chapter 4 reports the results from two complete action research cycles, including website redesign implementation, analytics data analysis, and qualitative interview findings.

Chapter 5 discusses the implications of the findings for each research question, examining the effectiveness of CAR-CE integration, the hierarchy of design elements in conversion optimization, and the role of social media in startup lead generation.

Finally, Chapter 6 concludes the thesis by summarizing key contributions to both practical startup optimization and academic understanding of action research methodologies in digital marketing contexts.

2 Literature review

2.1 Literature Review Method

The literature review employed inclusion and exclusion criteria while also relying on the researcher's judgment of the relevance and contribution of individual studies to the thesis topic. The goal was not to exhaustively capture all possible publications but to purposefully select works that provide a conceptual background and framework for the empirical study. Thus, the criteria functioned as guiding principles rather than strictly mechanical filters, ensuring both rigor and relevance in the final set of reviewed sources.

Publications were identified through Scopus and Scopus AI databases, with searches conducted using key terms related to user experience design, continuous experimentation, action research, web analytics, and digital marketing in startup contexts, with searches conducted using specific Boolean search queries targeting key concepts, as presented in Table 1.

Table 1: Primary Boolean Search Terms Used in Literature Review.

Concept Domain	Search Terms
User Experience Design	("user experience" OR "UX" OR "usability" OR "interaction design")
Continuous Experimentation	("continuous experimentation" OR "A/B testing" OR "split testing" OR "experimentation")
Action Research	("action research" OR "canonical action research" OR "participatory research")
Web Analytics	("web analytics" OR "digital analytics" OR "conversion optimization")
Digital Marketing	("digital marketing" OR "social media marketing" OR "LinkedIn marketing")
Context Terms	("startup" OR "early-stage" OR "small business" OR "entrepreneurship")
	("website optimization" OR "conversion rate" OR "lead generation")

Inclusion criteria encompassed: (1) publications from 2019 onwards, with exceptions made for seminal works of particular relevance to the research domain; (2) English-language publications only; (3) peer-reviewed journal articles, conference proceedings, and academic books indexed in major academic databases; (4) both empirical and theoretical studies contributing to understanding of UI/UX design, continuous experimentation, action research methodologies, or digital marketing effectiveness; and (5) studies with broad applicability rather than narrow geographic or industry-specific contexts. When multiple sources addressed similar topics, preference was given to publications with higher citation counts as indicators of academic impact and relevance.

Exclusion criteria included: (1) publications predating 2019 unless of exceptional theoretical significance; (2) non-English publications; (3) gray literature, including blogs, industry reports, and non-peer-reviewed sources not indexed in major academic databases; (4) studies with highly specific regional or cultural contexts that limited transferability; and (5) purely technical documentation without theoretical or empirical contribution.

2.2 Importance of User Experience (UX) and User Interface (UI) in Enhancing User Interaction, Engagement, and Satisfaction

User Experience (UX) and User Interface (UI) design are critical drivers of conversion rates in digital platforms [9]. According to one study, a well-designed UX can increase conversion rates by up to 400%, while a suitable UI can increase conversion rates by 200% [10].

The importance of UX and UI in enhancing user interaction, engagement, and satisfaction is well-documented across various studies. Enhanced UX/UI design, characterized by intuitive navigation, clear calls to action (CTAs), animations, and responsive performance, has been shown to significantly boost both engagement and conversion. For instance, a study on university admission websites found that a design pattern with easier access to the enrollment button led to a higher conversion rate (68.51%) compared to a less intuitive design (49.07%)[11]. A study by Akwukwuma [12] shows how integrating visually appealing and interactive elements in UIs, such as animations, leads to higher user satisfaction and engagement.

To design effective landing pages for AI startups that improve conversion rates and metrics, several key UI/UX principles can be adopted. For instance, persuasive elements such as headlines, trust indicators, benefit statements, and clear CTAs led to a conversion rate of 3.92% in an e-commerce study, which is significantly higher than the industry average (1.84%) [13]. Consistency and UI patterns create intuitive and familiar user experiences, which are crucial for improving user engagement [14]. Regarding readability and content analysis, it is recommended to ensure that the text on the landing page is easy to read and understand. A study showed that analyzing text readability could predict conversion rates, emphasizing the importance of clear and concise content [15].

Users form initial impressions of websites within seconds of viewing them, which significantly influences their likelihood to use and return to the site [16]. Structuring relevant information carefully to avoid overwhelming users is crucial. Clear and concise messaging helps users find the information they need without unnecessary delays [17]. Ram [17] also emphasizes the importance of incorporating a search feature and an FAQ section to enable customers to get to the information needed.

Slow web pages can lead to user abandonment, negatively affecting profits. Optimizing mobile web performance is crucial as it directly impacts user retention and satisfaction [18]. Performance optimizations such as reducing page load times and improving mobile compatibility are therefore associated with measurable gains in

user retention and sales.

2.3 Continuous Experimentation (CE) in Startups

Continuous Experimentation (CE) is defined as a systematic, hypothesis-driven process for improving digital products through rapid cycles of testing and validation. To accomplish this, different product variants can be exposed to different users to collect data about their behavior on the individual variants [4].

To define experiments in CE within startups, several important steps and considerations are essential. These steps include defining assumptions, formulating hypotheses, and identifying experiment objects such as Minimum Viable Products (MVPs) or Minimum Viable Features (MVsFs).

Since in CE many experiments are conducted to understand user behavior, and given the rise of experimentation in software engineering in general, Melegati [19] proposes a model in which the first step is to identify, prioritize, and specify hypotheses. Through a gray literature review of practitioner-proposed techniques for software startups, Melegati [19] identified five core activities that comprise Hypotheses Engineering: *elicitation* (identifying critical uncertain aspects through canvases, questions, or team sessions), *prioritization* (ranking hypotheses by risk and impact using qualitative matrices), *specification* (documenting hypotheses through structured templates), *analysis* (breaking down complex hypotheses and checking dependencies), and *management* (iterative refinement and tracking throughout the experimentation process). This systematic approach ensures that experiments are grounded in well-formed, testable hypotheses that can effectively guide product development decisions in uncertain startup environments.

2.4 Analytics and Mixed-Method Research

When redesigning AI-startup websites, the integration of web analytics and mixed-methods research can provide a comprehensive understanding of user behavior, preferences, and the effectiveness of design changes.

Web analytics is a powerful tool for understanding and optimizing user interactions with websites. It provides valuable insights that can drive business decisions, improve user experience, and enhance overall website performance [20]. Metrics such as bounce rate, session duration, and click-through rates are central to identifying friction points and validating improvements. By understanding user behavior, organizations can restructure their websites to enhance user experience, address security issues, and optimize bandwidth usage. This leads to better overall performance and higher conversion rates [6].

Mixed-methods research, combining qualitative insights (e.g., user interviews, polls) with quantitative data (web analytics, experiments), allows for a deeper understanding by contextualizing quantitative findings with qualitative data, leading to greater breadth and depth of insights [21]. This integrated approach provides a more complete picture of user needs and business outcomes.

The connection between analytics and mixed-methods research in redesigning websites lies in their complementary strengths [22]. Analytics provides quantitative insights into user behavior, while mixed-methods research adds qualitative depth, leading to a comprehensive understanding that drives effective and user-centric website redesigns. This integrated approach not only enhances decision-making but also addresses the unique challenges faced by AI startups in leveraging data for continuous improvement [23].

2.5 Digital Marketing and Social Media Integration

Digital marketing, particularly on B2B platforms, is a significant driver of lead generation for consulting startups. LinkedIn, for instance, is recognized as a valuable tool for lead generation and networking in B2B settings. It allows companies to leverage structured and unstructured data to identify new business opportunities and build quality business contacts, especially in international markets [24]. To improve website conversion rates and business outcomes using LinkedIn, several strategies can be employed, including profile optimization, content marketing, engagement in professional communities, and targeted outreach campaigns.

However, while social media can be used for customer acquisition strategies, startups often fail to maximize its potential for direct conversions [25]. Its usage is widely recognized as a powerful tool for creating and enhancing brand awareness. It allows startups to reach a broad audience and communicate their value propositions effectively [26]. Social media usage also significantly influences the brand image of startups, which in turn impacts their overall performance. This mediating role of brand image highlights the importance of social media in building a positive perception among consumers [27]. Given its nature, social media also facilitates word of mouth (WOM). High brand loyalty and strong positive WOM are key drivers of brand advocacy on social media, helping startups overcome challenges related to low brand awareness and limited financing capabilities [28]. More empirical evidence confirms how social media's primary function is to inform, interact, and promote rather than directly convert [29].

2.6 Literature Review Summary

The literature review reveals four interconnected domains that collectively inform website optimization strategies for early-stage startups. User experience and interface design research establishes that contemporary design principles significantly influence engagement metrics, with studies demonstrating conversion rate improvements of up to 400% through enhanced UX implementation [10]. However, these improvements depend critically on foundational elements including intuitive navigation, clear calls-to-action, and optimized performance rather than aesthetic appeal alone [11].

Continuous experimentation emerges as the methodological bridge connecting design theory to practical implementation, with Melegati's hypotheses engineering framework [19] providing systematic approaches for uncertainty identification and risk-based prioritization essential in resource-constrained environments. This experimental

rigor becomes particularly crucial when integrating analytics-driven decision making, where web analytics provides quantitative behavioral insights that require qualitative contextualization through mixed-methods approaches to achieve comprehensive user understanding [21].

Digital marketing theory, particularly in B2B contexts, positions social media platforms as brand awareness amplifiers rather than direct conversion channels [29], suggesting that integrated omnichannel strategies achieve superior outcomes compared to isolated digital efforts.

The synthesis of these perspectives establishes a conceptual framework where semantic clarity and information architecture serve as foundational requirements, upon which visual design improvements and social media integration can effectively operate. This framework emphasizes that successful website optimization requires systematic progression through communication clarity, structural organization, aesthetic enhancement, and multi-channel integration, with each layer dependent upon the effectiveness of its predecessors.

3 Research methods

3.1 Research Design

Action Research (AR) is an iterative methodology designed for organizational problem-solving through cycles of diagnosing, action planning, action acting, evaluation, and learning [30], as shown in Figure 1. During the diagnosing step, real problems are identified such as through interviews, observations, and data collection. During the action planning phase, strategies for intervention and improvement are developed. After that, in the action taking phase, solutions in industrial settings are implemented. Later, an evaluation is carried to measure the success of interventions using both qualitative and quantitative methods. Finally, in the last phase of learning, insights are documented and shared for future applications.

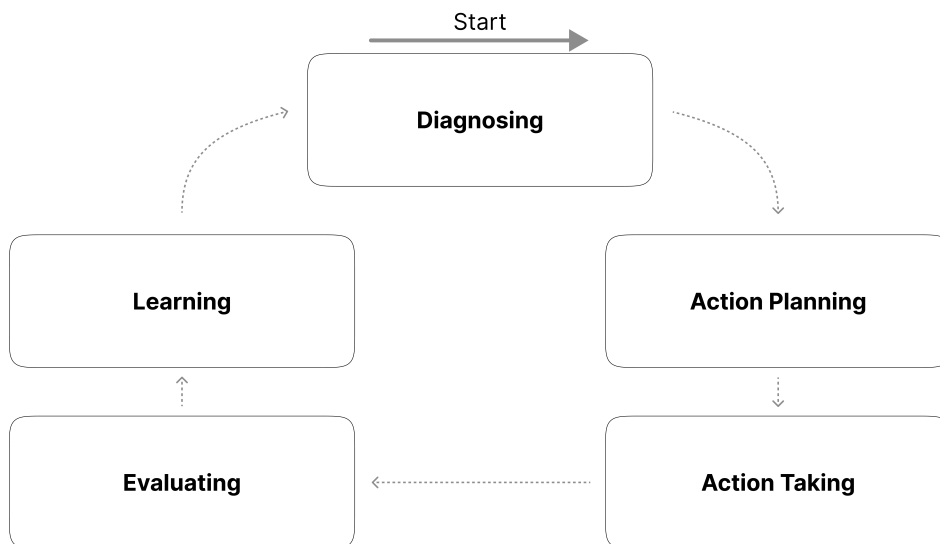


Figure 1: An action research cycle.

In information systems and software engineering, AR is used to address real-world challenges, foster organizational learning, and generate actionable knowledge. The integration of theory ensures that findings contribute beyond the specific context [8].

Canonical Action Research (CAR) refines this approach, emphasizing clear researcher-client agreements, theory-guided interventions, and dual contributions to practice and academic knowledge. The main point of CAR is to make real, meaningful change in an organization [8]. If no change happens, the research has failed in its primary goal. Key principles for rigorous CAR include: Alignment of objectives and roles between researchers and practitioners (“Researcher-Client Agreement”); Multiple iterations of diagnosing, intervening, evaluating, and reflecting (“Cyclical Process”); Use of focal and instrumental theories to guide and evaluate interventions (“Theory as a Guide”); Organizational improvement as a primary outcome (“Change Through Action”); Systematic documentation of insights and failures (“Learning

Through Reflection”) [31].

The RIGHT model (Rapid Iterative value creation Gained through High-frequency Testing) formalizes experiment-driven software development by tightly coupling business strategy with delivery through repeated Build-Measure-Learn loops [32]. Ideally, teams begin from a stable product vision, derive a flexible strategy with explicit assumptions, and translate the most uncertain, high-impact assumptions into testable hypotheses. Minimal, instrumented increments (MVPs/MVFs) are released to run field experiments; collected data is analyzed to decide whether to persevere, pivot, or refine assumptions, feeding the roadmap. Success depends on rapid, valid experiment design, trustworthy instrumentation and data handling, and systematic integration of findings into product and engineering decisions.

The project employs a CAR framework, organized into multiple cycles of diagnosing, planning, acting, evaluating, and reflecting, inspired by the RIGHT model. This structure allows for systematic, theory-driven interventions that are directly responsive to organizational needs. Each cycle incorporates CE principles, using web analytics and controlled tests to validate assumptions and guide improvements. Care is taken to distinguish between research-level questions (addressed by AR) and product-level optimization (guided by CE), acknowledging their connected but distinct contributions.

3.2 Data Collection Methods

A multi-faceted data collection approach was implemented to gather comprehensive insights into user behavior and website performance throughout the research period. This methodology combined quantitative analytics with qualitative user feedback to establish a robust foundation for iterative design improvements and conversion optimization strategies.

3.2.1 Interviews and Observations

Short-form interviews and informal user observations were conducted to identify critical pain points in the user journey and inform hypothesis generation for subsequent design iterations. These qualitative sessions provided contextual understanding of user motivations, frustrations, and decision-making processes that quantitative metrics alone could not capture. The interview protocol (Table 2) focused on user perceptions of site trustworthiness, value proposition clarity, and navigation efficiency to complement the behavioral data collected through analytics platforms.

The interview procedure received a positive assessment under Approval nr 251557 of the Ethics Committee of Computer and Information Sciences (CIS) of the University of Twente.

3.2.2 Web Analytics Implementation

PostHog analytics platform [33] was chosen to systematically track user interactions across all website touchpoints. Key performance indicators monitored included conversion rates, bounce rates, session durations, and more. This comprehensive

Table 2: Interview Protocol for Website Usability and Message Clarity Assessment.

Phase	Activity	Protocol/Questions	Duration
Introduction & Consent	Welcome & Setup	<ul style="list-style-type: none"> • Welcome participant and establish environment • Confirm technical setup (if remote) • Review consent form (Figure A1) and obtain confirmation • Remind about confidentiality and no recording 	2-5 min
	Consent Confirmation	<ul style="list-style-type: none"> • Confirm voluntary participation • Remind about right to withdraw at any time 	
Website Exploration	Free Exploration	<ul style="list-style-type: none"> • "Please explore the website freely for a few minutes" • Observer takes notes on navigation patterns, hesitation points, and behavioral indicators 	1-7 min
Semi-Structured Interview	Core Question 1	"What do you think this company does?"	10-15 min
	Core Question 2	"What makes you think that?"	
	Core Question 3	"What was clear or unclear?"	
	Open Discussion	Open-ended discussion prompts based on participant responses	
Closing	Debrief	<ul style="list-style-type: none"> • Thank participant • Brief explanation of research purpose • Confirm data usage and anonymity 	2-3 min
Total Session Duration			15-30 min

tracking infrastructure enabled real-time assessment of user engagement quality and identification of potential optimization opportunities within the conversion funnel. The analytics framework was configured to capture both macro-conversions (form submissions, appointment bookings) and micro-conversions (page visits, time on page) to provide granular insights into user behavior patterns.

To ensure GDPR compliance while using PostHog, best practices from the official documentation were followed. PostHog Cloud EU (Frankfurt) was used to keep all analytics data within EU jurisdiction and disabled IP address capture. A cookie banner and consent mechanism were implemented, ensuring PostHog scripts only initialized after users gave unambiguous consent, as required under GDPR. In addition, PostHog was configured to anonymize or mask potentially identifiable fields before storage.

3.2.3 LinkedIn Performance Analysis

Comprehensive engagement metrics analysis was conducted across the company's LinkedIn profile to establish correlations between marketing activities and website performance outcomes. This analysis tracked click-through rates, referral traffic quality, and conversion attribution from social channels to understand the effectiveness of different promotional strategies in driving qualified website traffic and subsequent user actions.

3.3 Analysis and Evaluation

The evaluation methodology employed a systematic mixed-methods approach combining quantitative analytics with qualitative thematic analysis to ensure comprehensive assessment of intervention effectiveness.

Statistical comparisons between cycles enabled identification of performance trends and intervention impacts, while cross-platform validation through LinkedIn analytics provided additional engagement metrics.

The identification and measurement of Key Performance Indicators (KPIs) were central to both the practical and academic aims of this study (Table 3). On the business side, KPIs serve to quantify progress toward the primary goal of increasing the website's metrics. From a research perspective, they provide empirical grounding for evaluating interventions implemented during each AR cycle. Moreover, KPIs give insights into how CE and user-centered design affect metrics in early-stage consulting startups websites.

These KPIs were identified and implemented iteratively throughout the research process. The specific metrics used in each cycle are detailed in the corresponding results sections, reflecting the adaptive nature of the CAR methodology where measurement approaches evolved based on emerging insights and organizational needs.

The KPIs selected for this project capture not only transactional outcomes such as lead generation, but also the behavioral, perceptual, and methodological dynamics that generate those outcomes. Each metric has been chosen for its relevance to one or more of the research questions and is designed to offer insight into user engagement, website effectiveness, and experimentation progress.

3.3.1 Web Analytics Analysis (Cycles 1 and 2)

Quantitative analysis utilized PostHog analytics data to track KPIs including conversion rates, bounce rates, session durations, and traffic attribution across multiple measurement periods.

The primary objective was to assess the website's ability to effectively communicate the company's services in order to leave a clear message to the visitors. A clear message of what the company offers can convert a potential client into an inbound lead, in contrast to an unclear website that does not effectively communicate to a potential client that the company might offer something for them. Conversion is defined here

Table 3: Key Performance Indicators (KPIs) Used Throughout the Study.

KPI Category	Metric	Cycle(s) Used	Research Question
User Acquisition & Engagement	Unique Users	Cycles 1, 2	RQ1, RQ3
	Total Sessions	Cycles 1, 2	RQ1
	Session Duration (average)	Cycles 1, 2	RQ1, RQ2
	Bounce Rate	Cycles 1, 2	RQ1, RQ2
	Pages per Session	Cycles 1, 2	RQ2
	Peak Daily Sessions	Cycles 1, 2	RQ1, RQ3
Conversion & Lead Generation	Qualified Leads (total)	Cycles 1, 2	RQ2
	Form Submissions	Cycles 1, 2	RQ2
	Call Booking Clicks	Cycles 1, 2	RQ2
	Micro-conversions	Cycles 1, 2	RQ2
Traffic Sources & Attribution	Traffic Source Distribution	Cycles 1, 2	RQ3
	Referral Traffic Quality	Cycles 1, 2	RQ3
	Cross-site Referrals	Cycle 2	RQ2, RQ3
User Demographics & Behavior	Geographic Distribution	Cycles 1, 2	RQ1, RQ3
	Device Preference	Cycles 1, 2	RQ1
	Landing Page Performance	Cycles 1, 2	RQ2
LinkedIn Performance	Profile Visits	Cycles 1, 2	RQ3
	Page Views	Cycles 1, 2	RQ3
	Impressions	Cycles 1, 2	RQ3
	Reactions	Cycles 1, 2	RQ3
	Visitor Demographics (profession)	Cycles 1, 2	RQ3
Qualitative Indicators	Message Clarity Perception	Cycle 2	RQ1, RQ2
	Value Proposition Understanding	Cycle 2	RQ2
	Navigation Usability	Cycle 2	RQ2
	Trust and Credibility Perception	Cycle 2	RQ2
Process & Methodology	Completed Experimentation Cycles	Throughout	RQ1
	Hypothesis Validation Rate	Cycles 1, 2	RQ1
	Intervention Implementation Success	Cycles 1, 2	RQ1

as any visitor who books a consultation call, completes a contact form, or otherwise initiates a meaningful sales interaction.

Complementing this, micro-conversions were also tracked. These included interactions such as clicking on “Book a Call” or “Contact Us,” which may signal intent even if they did not result in completed lead forms. Tracking the micro-conversion rate provides early indications of interest and allows for more nuanced analysis of

drop-off points in the user journey.

To assess the effectiveness of different acquisition channels, the lead source breakdown was also recorded, allowing conversion rates to be compared across traffic origins such as organic search, direct visits, and LinkedIn referrals. This enabled an evidence-based understanding of which platforms contribute most effectively to business outcomes.

To interpret how users interact with the website before they convert, or abandon, the study tracked a series of behavioral indicators. The bounce rate, defined as the percentage of users who exit the site after viewing only one page, provided a surface-level measure of first-impression effectiveness. When paired with session duration and pages per session, it became possible to identify whether visitors were engaging with the site's content or losing interest prematurely. These behavioral metrics supported the second research question, which seeks to identify which specific design and content elements demonstrate strongest impact on lead qualifications and conversion rates.

3.3.2 Qualitative Interview Analysis (Cycle 2)

In addition to quantitative metrics, qualitative KPIs were employed to capture how users perceived the site in terms of trust, clarity, and value. These factors are particularly important in consulting services, where trust and perceived expertise often influence purchasing decisions more than pricing or functionality alone.

Through short interviews, users were asked about their perceptions of the site's trustworthiness, as well as whether they understood the value proposition quickly. Patterns in confusion points, brand credibility, and user motivations or frustrations were systematically coded and integrated into the reflection phase of the 2nd research cycle. This ensured that user feedback directly informed both experimental design and strategic direction.

Qualitative evaluation followed Braun and Clarke's six-phase thematic analysis framework for interview data, ensuring rigorous pattern identification within user feedback. The credibility and validity of interview findings were evaluated against established qualitative research standards outlined by Merriam and Tisdell [34].

These indicators played a critical role in diagnosing barriers to conversion that analytics alone missed. Moreover, they contributed to a richer, mixed-method understanding of user experience and decision-making behavior.

3.3.3 LinkedIn Performance Analysis (Cycles 1 and 2)

Given the project's intention to integrate digital marketing with website optimization, several KPIs tracked the impact of LinkedIn. Traffic from social media was measured using referral data, while conversion from social traffic evaluated the extent to which social visitors ultimately become leads. These figures shed light on the effectiveness of social content in not only generating visibility but also driving qualified traffic.

Engagement metrics such as likes, shares, and comments on LinkedIn posts were recorded to gauge content resonance. More importantly, the click-through rate

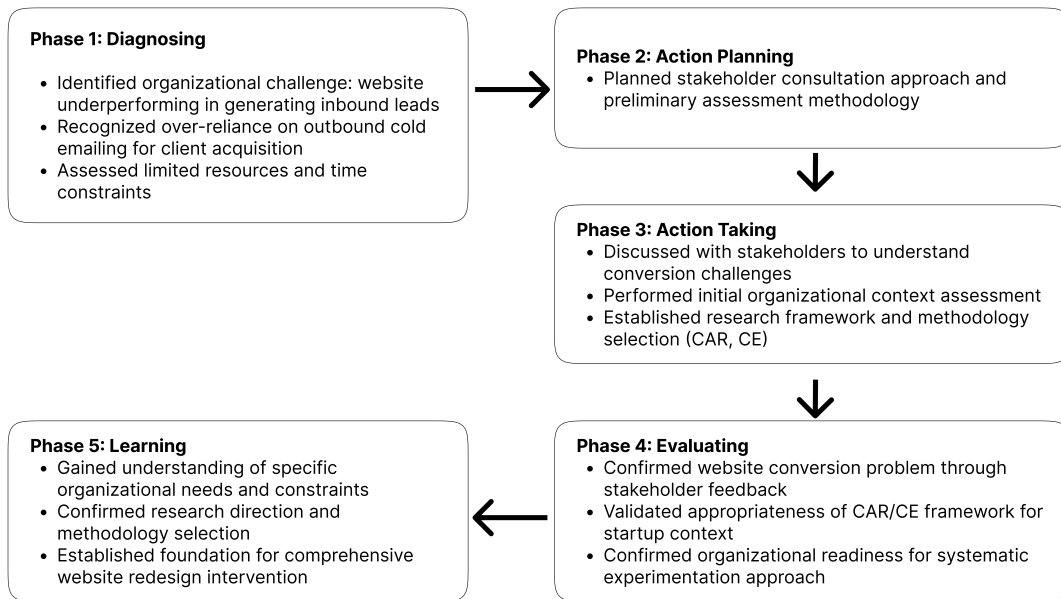


Figure 2: Overview of the 5 steps of the 0th AR (Mar 29 - Apr 21 2025).

from social to website revealed how well social posts motivated users to visit the site. Differentiation between personal, narrative-driven posts and more technical or promotional content was used to assess post type performance, feeding into the third research question: How do social media channels and content types influence website visitation?

3.3.4 Cross-Cycle Evaluation

Regular stakeholder consultations ensured findings remained aligned with organizational objectives and practical implementation constraints. Ethical considerations included informed consent (Appendix A) for all interview participants, adherence to data privacy compliance standards, and transparent communication of research purposes and data usage to all stakeholders involved in the study.

Finally, to assess the progress and effectiveness of the continuous experimentation approach itself, a set of process-oriented KPIs were monitored. These included the number of completed experimentation cycles, the average duration of each cycle, and the number of website interventions implemented. Such metrics provided a measure of the project’s internal rhythm and responsiveness.

Equally important was to reflect on whether the hypotheses being tested were well-formed and whether the experimentation process can be translated into actionable learning.

4 Results

The following cycles were structured according to CAR principles. Following the "Researcher-Client Agreement" principle, formal stakeholder consultations were conducted to establish clear roles, responsibilities, and shared objectives between the research team and organizational decision-makers. The "Cyclical Process" model guided the planning of iterative intervention cycles, with each cycle designed to follow the five-phase structure: diagnosing, action planning, action taking, evaluating, and learning. The "Theory" principle served to ensure that literature was used as the primary guide for interventions, while CE principles, particularly inspired by the RIGHT model [32], served as the instrumental theory for hypothesis-driven testing within subsequent cycles, with controlled experiments, data analysis, and evidence-based decision. The plannings ensured that "Changes Through Action" were the primary outcome, with systematic "Learning" through reflection documented to contribute to both practical and academic knowledge.

4.1 Organizational Problem Identification and Framework Selection

A preliminary action research cycle was conducted to establish the foundational understanding of organizational challenges and to validate the appropriateness of the selected research methodology, as shown in Figure 2. This lightweight cycle served as a precursor to the comprehensive website redesign intervention, focusing on problem diagnosis and methodological framework selection rather than direct implementation activities.

4.1.1 Phase 1: Diagnosing

The diagnostic phase was initiated through systematic organizational assessment to identify core business challenges affecting the startup's growth trajectory. Primary stakeholder consultations revealed that the company's current client acquisition strategy relied predominantly on outbound cold emailing approaches, with minimal contribution from organic website traffic ("We're spending about 80% of our business development time on cold emailing", as one of the company's co-founders mentioned). This dependency on outbound methods was identified as a potential scalability constraint, particularly as the organization sought to expand its client base without proportionally increasing manual outreach efforts.

Initial assessment of the existing website infrastructure indicated limited conversion optimization and absence of systematic analytics tracking. The organizational context analysis revealed typical early-stage startup constraints, including resource limitations, time pressures, and competing priorities that had previously prevented comprehensive digital presence optimization. During the first meeting, for instance, one co-founder stated that "[They] know [their] website looks outdated, but [they] have been so focused on delivering client projects that [they] never had time to fix it properly." These findings aligned with established patterns in startup environments where immediate revenue

generation activities often take precedence over longer-term digital infrastructure development.

Finally, by discussing findings from a study that analyzed five startups in Finland with varying degrees of CE usage [35] and analyzing the company's resources constraints, one of the co-founders decided that "[They] can dedicate maybe 10-15 hours per week to this, but it needs to show results quickly, because looks like it can - [they] can't afford long development cycles."

4.1.2 Phase 2: Action Planning

The action planning phase focused on methodological framework selection and research approach design rather than specific technical interventions. CAR was identified as the appropriate research methodology due to its emphasis on practical organizational problem-solving while maintaining academic rigor. The integration of CE principles was planned to address the startup's need for rapid iteration and evidence-based decision making.

Preliminary research design considerations included the establishment of mixed-methods data collection approaches, combining quantitative analytics with qualitative feedback to ensure comprehensive understanding of user behavior and organizational needs. The planning phase also involved assessment of available technological resources and identification of potential development approaches that would align with organizational constraints and capabilities.

4.1.3 Phase 3: Action Taking

The action taking phase involved formal stakeholder engagement and organizational commitment to the research process. Short meetings with the company's co-founders were conducted with key organizational decision-makers to validate problem identification and secure support for the proposed intervention approach. These consultations confirmed the strategic importance of website conversion optimization for organizational growth objectives and one co-founder emphasized that "It could be the perfect moment to spend some time on [their] website since [they] are growing and need to improve [their] image").

Preliminary user research activities were initiated to understand current website performance limitations and user experience barriers. Initial observations of existing user interactions with the website were analyzed to establish baseline understanding prior to comprehensive analytics implementation. Organizational readiness assessment was completed to ensure adequate resources and commitment for sustained research engagement.

4.1.4 Phase 4: Evaluating

The evaluation phase involved systematic assessment of organizational problem validation and methodology appropriateness. Stakeholder feedback confirmed that website conversion optimization represented a critical business priority with measurable

impact potential on lead generation outcomes. The preliminary assessment validated that current website performance was indeed below organizational expectations (0 bookings since the website ever existed).

Methodological appropriateness was evaluated through consideration of organizational context (AI-consulting startup who wants to improve engagement of visitors of their website), resource availability (one intern software engineer responsible of design, analytics, and development of the website), and business objectives alignment (at least three bookings within the website in the first 4-6 months). The CAR framework was confirmed as suitable for addressing the dual requirements of practical business improvement and academic knowledge contribution. Resource assessment indicated sufficient organizational capacity for sustained engagement with the proposed research approach.

4.1.5 Phase 5: Learning

Cycle 0 clarified the problem, confirmed the CAR+CE fit, and produced baselines, hypotheses, and guardrails (validity and GDPR) to run disciplined, small-scope experiments in subsequent cycles. Organizational commitment to systematic, evidence-based website optimization was established as a foundational requirement for research success. The importance of stakeholder alignment and clear communication of research objectives emerged as essential factors for maintaining organizational engagement throughout iterative improvement cycles.

Key methodological insights included validation of the CAR framework's appropriateness for startup environments and confirmation that CE principles could be effectively integrated within academic research constraints. The preliminary cycle also established that website conversion optimization represented a suitable domain for applying Human-Computer Interaction (HCI) principles within real organizational contexts, providing both practical value and academic learning opportunities.

The successful completion of this preliminary cycle provided confidence in proceeding with comprehensive website redesign interventions while maintaining systematic documentation and evaluation processes required for rigorous academic research.

4.2 Hypotheses Engineering Framework Application

Hypotheses were included to ensure that the study followed a systematic, testable, and falsifiable research design. In the context of CAR, hypotheses provide measurable targets that guide each intervention cycle and allow evaluation of whether observed changes can be linked to specific design or content decisions.

Following Melegati's systematic approach to hypotheses engineering in startup environments [19], this research employed a structured five-phase process to ensure experiments were grounded in well-formed, testable hypotheses that could effectively guide website optimization decisions. The framework's emphasis on uncertainty identification and risk-based prioritization proved particularly valuable in the resource-constrained startup context, where experimental failures carry significant opportunity

costs.

4.2.1 Initial Hypothesis Development and Refinement Process

The application of Melegati's framework resulted in significant evolution of hypotheses from initial formulation to final implementation (Table 4). The original hypothesis set contained eight detailed hypotheses with extensive theoretical grounding and multiple sub-components. However, the prioritization and analysis phases revealed that this initial approach was overly complex for the resource-constrained startup environment and contained dependencies that would complicate experimental design.

Elicitation activities were conducted through stakeholder consultation sessions and preliminary website assessment, identifying critical uncertain aspects such as the effectiveness of UI modernization, conversion funnel optimization, and multi-channel marketing integration. The initial formulation included extensive theoretical justification for each hypothesis, reflecting academic rigor but potentially obscuring practical implementation requirements.

Prioritization revealed several issues with the original hypothesis structure. First, the detailed theoretical grounding, while academically sound, created unnecessarily complex success criteria that would be difficult to measure within the one-month cycle timeframes. Second, multiple sub-hypotheses within single constructs (such as H5 containing both interview effectiveness and mixed-methods integration) created evaluation challenges. Third, resource limitations necessitated focusing on the most actionable and measurable aspects of each hypothesis.

Specification led to systematic simplification and consolidation of hypotheses. The original H1 (User Interface Modernization) was streamlined from detailed theoretical justification to a clear, measurable prediction: "Implementation of contemporary UI/UX design principles will result in good user engagement metrics and bounce rate lower than 50%." Similarly, H2 (Conversion Funnel Optimization) was simplified from complex persuasive design theory to a specific target: "Strategic placement and design optimization of call-to-action elements will increase qualified leads from 0 to 3 during the initial measurement period."

Analysis revealed critical dependencies that influenced hypothesis sequencing. The original H5 contained two distinct components: message clarity investigation and mixed-methods validation. The analysis phase identified that message clarity was a prerequisite for navigation optimization, leading to the separation of these concerns and the recognition that qualitative research findings would inform subsequent quantitative interventions.

Management encompassed iterative refinement based on stakeholder feedback and practical constraints. Company co-founders expressed preference for concise, actionable hypotheses over extensively theorized predictions. This feedback led to the elimination of detailed theoretical justifications within hypothesis statements while maintaining the underlying academic rigor in the methodology design. The evolution from complex, multi-component hypotheses to streamlined, testable predictions reflected the startup environment's need for rapid iteration and clear success criteria.

The systematic application of Melegati's framework thus transformed an initially

Table 4: Hypothesis Evolution Through Melegati’s Framework Application.

Phase	Original Approach	Issues Identified	Refined Approach
Elicitation	8 detailed hypotheses with multiple sub-components	Overly complex structure obscured practical implementation requirements	7 streamlined hypotheses focused on core uncertainties and measurable outcomes
Prioritization	Equal weight given to all hypotheses regardless of implementation complexity	Resource constraints and measurement challenges not adequately considered	High-impact, low-risk hypotheses prioritized for early cycles
Specification	Extensive theoretical justification embedded within hypothesis statements	Complex success criteria difficult to measure within one-month cycles	Clear, measurable predictions with specific targets (e.g., "bounce rate < 50%", "3+ qualified leads")
Analysis	Multiple sub-hypotheses within single constructs (e.g., H5 containing interview + mixed-methods)	Evaluation challenges and unclear dependencies between interventions	Separated concerns; identified prerequisite relationships (H5 before H6)
Management	Academic rigor prioritized over practical implementation needs	Stakeholder preference for concise, actionable hypotheses	Maintained theoretical foundation while streamlining presentation for startup context

academic hypothesis structure into a practically oriented experimental design that maintained theoretical rigor while addressing the specific constraints and requirements of early-stage startup environments. This evolution demonstrates the framework’s value in bridging academic research standards with entrepreneurial execution needs.

4.2.2 Final Hypothesis Structure

The refined hypothesis structure emerged from this systematic application of Melegati’s framework, resulting in seven core hypotheses distributed across two action research cycles. Each hypothesis was designed to address specific uncertainties while remaining measurable within the resource and time constraints of the startup environment. The evolution from complex theoretical constructs to actionable predictions illustrates the framework’s effectiveness in translating academic rigor into practical experimental design suitable for early-stage organizational contexts.

Table 5 demonstrates the transformation of the User Interface Modernization hypothesis from extensive theoretical justification to a clear, measurable prediction with specific success criteria.

The evolution shown in Table 6 illustrates how the Conversion Funnel Optimization

Table 5: H1 Evolution: User Interface Modernization Hypothesis.

Original Formulation	Final Implementation
<p>User Interface Modernization Hypothesis: The implementation of contemporary UI/UX design principles, including responsive design patterns and optimized visual hierarchy, will significantly improve user engagement metrics (session duration, pages per session) and reduce bounce rates compared to the original website design.</p>	<p>H1 (User Interface Modernization): Implementation of contemporary UI/UX design principles will result in good user engagement metrics and bounce rate lower than 50%.</p>

Table 6: H2 Evolution: Conversion Funnel Optimization Hypothesis.

Original Formulation	Final Implementation
<p>Conversion Funnel Optimization Hypothesis: The strategic placement and design optimization of call-to-action elements, combined with streamlined user flows toward conversion points, will increase the number of unique visitors who converted into qualified leads from 0 to 3 during the initial measurement period.</p>	<p>H2 (Conversion Funnel Optimization): Strategic placement and design optimization of call-to-action elements will increase qualified leads from 0 to 3 during the initial measurement period.</p>

hypothesis was simplified from complex persuasive design theory to a specific, measurable target.

Table 7 shows the refinement of the Analytics-Driven Decision Making hypothesis, reducing complex structures into streamlined hypotheses while maintaining the core focus on systematic data collection capabilities.

The transformation demonstrated in Table 8 shows how the Multi-Channel Traffic Integration hypothesis was streamlined from complex social proof theory to a clear prediction about traffic source performance.

Table 9 illustrates the separation of the originally dual-component H5 hypothesis, focusing specifically on message clarity investigation while removing the mixed-methods validation component.

The refinement shown in Table 10 demonstrates how the Navigation Optimization hypothesis was simplified from cognitive load theory to a specific, measurable prediction about user behavior.

Table 11 shows the division of the originally complex H7 hypothesis into two

Table 7: H3 Evolution: Analytics-Driven Decision Making Hypothesis.

Original Formulation	Final Implementation
<p>Analytics-Driven Decision Making Hypothesis: The implementation of comprehensive analytics tracking from project initiation will enable data-driven identification of conversion barriers and optimization opportunities that would remain undetected through qualitative assessment alone.</p>	<p>H3 (Comprehensive Analytics Implementation): Systematic tracking from project initiation will enable identification of traffic patterns and conversion barriers across multiple channels.</p>

Table 8: H4 Evolution: Multi-Channel Traffic Integration Hypothesis.

Original Formulation	Final Implementation
<p>Multi-Channel Traffic Integration Hypothesis: The coordinated promotion across LinkedIn, Instagram, and organic search channels will generate diversified traffic sources, with social media referrals demonstrating higher engagement metrics (session duration, page depth) due to pre-qualified interest from professional networking contexts.</p>	<p>H4 (Multi-Channel Traffic Integration): Coordinated promotion on LinkedIn and organic search channels will generate diversified traffic sources, with LinkedIn referrals generating higher traffic.</p>

distinct, testable components: H7a focusing on product separation effects and H7b addressing offline-to-online integration strategies.

The systematic application of Melegati’s framework resulted in several consistent transformations across all hypotheses. Clearer success criteria transformed abstract concepts into specific, measurable targets such as "bounce rate < 50%" and "25% increase." Complex constructs were separated where necessary, notably splitting H7 into H7a and H7b to address distinct aspects of product separation and offline-to-online integration. Redundancy was eliminated by removing dual-component structures, particularly in H5 which originally combined interview effectiveness with mixed-methods validation. The scope was reduced to focus on core uncertainties most relevant to immediate business needs and resource constraints, while improved actionability ensured each hypothesis could be tested within one-month cycle timeframes with available resources.

Table 9: H5 Evolution: Message Clarity and Mixed-Methods Hypothesis.

Original Formulation	Final Implementation
<p>Conducting structured user interviews will reveal specific communication gaps in the website’s value proposition that quantitative analytics alone cannot identify, leading to actionable insights for improving message clarity and reducing user confusion about service offerings. The integration of qualitative interview data with existing quantitative analytics will reveal previously undetected user experience barriers and provide more nuanced insights into conversion optimization opportunities than either method would yield independently.</p>	<p>H5: Structured user interviews will reveal specific communication gaps that quantitative analytics alone cannot identify, leading to actionable insights for improving message clarity.</p>

Table 10: H6 Evolution: Navigation Optimization Hypothesis.

Original Formulation	Final Implementation
<p>The modification of the navigation item from "Portfolio" to "Our Projects" will increase click-through rates to the services section by at least 25% compared to the previous measurement period, as clearer navigation labels reduce cognitive load and improve information findability.</p>	<p>H6: Modification of navigation from "Portfolio" to "Our Projects" will increase visits to the projects section by at least 25%.</p>

4.3 Hypotheses after Cycle 0

Based on the evaluation and learning phase of the 0th cycle, the following hypothesis have been formulated to be investigated during Cyce 1.

H1 (User Interface Modernization): Implementation of contemporary UI/UX design principles will result in good user engagement metrics and bounce rate lower than 50%. H1 contributes to investigate RQ1 (UI/UX Design Improvements).

H2 (Conversion Funnel Optimization): Strategic placement and design optimization of call-to-action elements will increase qualified leads from 0 to 3 during the initial measurement period. H2 contributes to investigate RQ2 (Conversion Funnel Optimization).

Table 11: H7 Evolution: Product Separation and Offline-to-Online Integration Hypothesis.

Original Formulation	Final Implementation
<p>The migration of LEVELS OS to a dedicated website (operatororesicurezza.it) will improve conversion rates for both the main consulting website and the product-specific site by reducing cognitive overload and enabling targeted marketing campaigns, while maintaining referral traffic between properties. The coordinated launch campaign for LEVELS OS (exhibition presence, printed materials, QR codes, dedicated website) will generate measurable cross-channel attribution and demonstrate the effectiveness of integrated offline-to-online marketing strategies in B2B contexts.</p>	<p>H7a: Migration of LEVELS OS to a dedicated website will improve conversion rates for both sites by reducing cognitive overload while maintaining referral traffic between properties.</p> <p>H7b: The coordinated launch campaign for LEVELS OS (exhibition presence, printed materials, QR codes) will generate measurable cross-channel attribution and demonstrate effectiveness of integrated offline-to-online marketing strategies.</p>

H3 (Comprehensive Analytics Implementation): Systematic tracking from project initiation will enable identification of traffic patterns and conversion barriers across multiple channels.

H4 (Multi-Channel Traffic Integration): Coordinated promotion on LinkedIn and organic search channels will generate diversified traffic sources, with LinkedIn referrals generating higher traffic. H3 and H4 contribute to investigate RQ3 (Social Media Integration).

4.4 Website Redesign and Analytics Implementation

The first AR cycle focused on comprehensive website redesign and analytics implementation to address the conversion optimization challenges identified in the preliminary cycle. This cycle involved systematic technical assessment of the existing website infrastructure, followed by rapid development and deployment of a modernized website using AI-assisted development tools and comprehensive analytics tracking, as shown in Figure 3. The intervention was implemented over a one-month period (April 29 - May 29, 2025), during which user behavior data was systematically collected and analyzed to evaluate the effectiveness of UI/UX improvements and conversion optimization strategies. The cycle demonstrated successful user acquisition with 844 unique users and positive engagement metrics, while also revealing specific areas for optimization in subsequent research iterations.

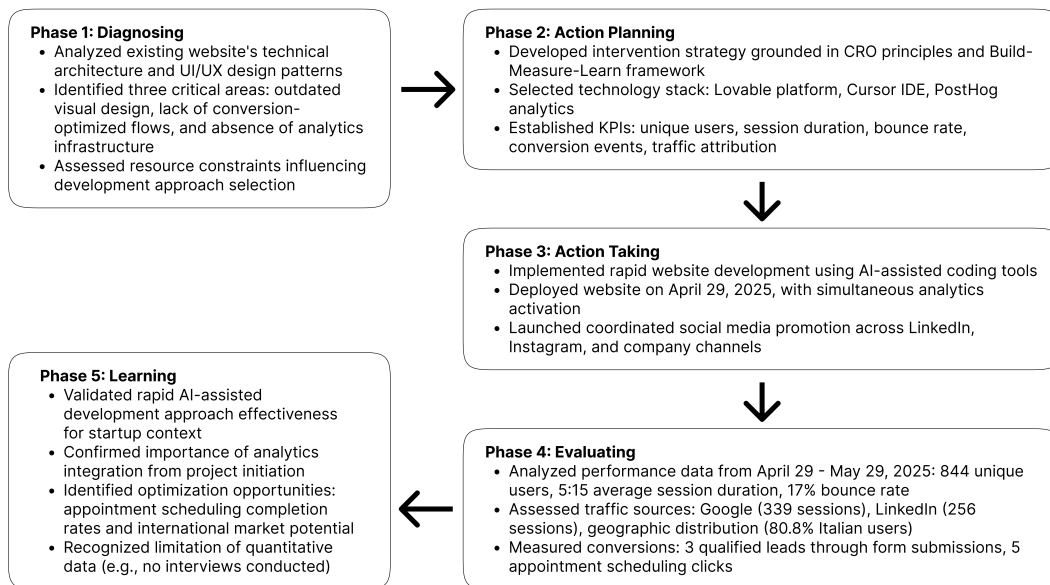


Figure 3: Overview of the 5 steps of the 1st AR (Apr 29 - May 29 2025).

Data collection was conducted using PostHog analytics platform.

4.4.1 Phase 1: Diagnosing

The diagnostic phase focused on detailed technical assessment of the existing website infrastructure. Analysis of the existing website's technical architecture, user interface design patterns, and poor quality of systematic analytics tracking was conducted. The diagnosis revealed three critical areas requiring intervention: (1) outdated visual design inconsistent with modern UI/UX principles, (2) lack of conversion-optimized user flows and call-to-action elements, and (3) poor analytics infrastructure for data-driven decision making ("We have some data stored in a database that we expressively tracked within the code but they are not useful. I would rather start from scratch. We tracked wrong data in the wrong way because we didn't think about analytics when we were still in our very early-stages", company's co-founder).

The organizational context assessment indicated a startup environment requiring rapid iteration cycles, which influenced the selection of development tools and methodologies. Resource constraints and time limitations were identified as key factors that would shape the intervention approach, leading to the adoption of template-based development rather than custom design system creation.

4.4.2 Phase 2: Action Planning

The action planning phase involved developing a comprehensive intervention strategy grounded in UI/UX design principles and web analytics theory described in Section 2.2 and 2.4.

Based on these principles, the interface will adopt contemporary design patterns

with prominent call-to-action elements in the navigation bar and within key sections, supported by clear headlines that state content and value propositions. The information architecture will follow consistent page structures (headline + CTA, scannable hierarchy, unified footer) and use standardized color palettes and typography for visual coherence. Trust indicators (client testimonials and partner logos) will be integrated on the landing page. FAQ sections will be placed at the bottom of key pages to address common queries, and no site-wide search will be implemented. The focal theory guiding this phase centered on conversion rate optimization (CRO) principles, which posit that systematic improvements to user interface elements, information architecture, and persuasive design patterns can measurably increase user conversion rates [36].

The instrumental theory selected for implementation guidance was the Build-Measure-Learn framework [37], which emphasizes rapid prototyping, data collection, and iterative refinement. This framework was deemed appropriate for the startup context where speed of execution and validated learning take precedence over extensive upfront planning.

Technical planning decisions included: (1) selection of Lovable [38] platform for rapid template-based development, (2) development using Cursor IDE [39] with AI-support to speed up development, (3) integration with existing email infrastructure to maintain operational continuity, (4) implementation of PostHog analytics platform for comprehensive user behavior tracking, and (5) establishment of social media promotion strategy across LinkedIn, Instagram, and company channels.

Overall, decision have been taken based on literature and the researcher and stakeholders' personal experiences. For instance, it was mentioned by one of the co-founders how "Cursor really sped up development. In other projects, what would have taken us weeks, we accomplished in days", which suggested familiarity with and effectiveness of the tool. Lovable and PostHog were chosen under suggestion of one of the co-founders who actively followed these two startups on social media and suggested that the products could have suited the company's requirements and available resources ("I know two startups who make products we might try out: Lovable for Low-Code development and PostHog for analytics. The first one seems to produce high-quality code and design in a few minutes. The second seems to have many features and low pricing.").

Key performance indicators (KPIs) were established to measure intervention effectiveness: unique users, session duration, bounce rate, conversion events through form submissions, appointment scheduling clicks, and traffic source attribution. These metrics were selected to provide comprehensive visibility into user acquisition, engagement, and conversion funnel performance.

4.4.3 Phase 3: Action Taking

The intervention implementation commenced with rapid website development using the selected technology stack. Development activities were conducted primarily using Cursor. Technical implementation included migration from Vite [40] to Next.js framework [41] to ensure compatibility with existing backend infrastructure.

Based on the literature review findings and team experience, the website re-design implemented several key UI/UX principles (described in Phase 2) to optimize conversion performance. Performance optimization utilized Next.js framework and React best practices to ensure responsive mobile compatibility. The landing page emphasized immediate visual impact through prominent headlines, primary CTAs, and an introductory team video designed to convey professional competence and organizational culture, supplemented by explanatory diagrams and imagery throughout the site to enhance conceptual understanding.

The website was deployed on April 29, 2025, with simultaneous activation of analytics tracking and promotional campaign launch. Social media promotion was executed across multiple channels, with content distribution through personal and corporate LinkedIn profiles, Instagram presence, and targeted engagement with relevant professional networks.

4.4.4 Phase 4: Evaluating

The evaluation phase encompassed systematic analysis of collected data during the initial measurement period (April 29 - May 29, 2025). Performance assessment utilized the established KPI framework to evaluate website performance. Overall, two of the four hypotheses were supported by the experiments conducted, as shown in Table 12. Results were summarized in Tables 13-19.

Table 12: Cycle 1: Hypothesis Validation Results.

Hypothesis	Target	Supported
H1: UI Modernization	Bounce rate < 50%	Inconclusive (17%)
H2: Conversion Optimization	3+ qualified leads	Yes (4 leads)
H3: Analytics Implementation	Valuable insights	Yes
H4: Multi-Channel Traffic	LinkedIn > Google	No

User acquisition metrics showed 844 unique users recorded during the initial month (Table 13) and average session duration of 5 minutes and 15 seconds. There is no one-size-fits-all answer to what constitutes a good average session duration. It varies significantly based on the analytics tools used [42], the methods of session identification, and the specific context of the website [43]. Generally, higher session durations are indicative of better user engagement, but it is crucial to benchmark against industry standards and customize session tracking methods to specific needs [44].

Bounce rate analysis showed a value of 17%. Like for the average duration sessions, there is no universally "good" bounce rate percentage. Again, the acceptable bounce rate can vary depending on the website's purpose, industry, and user behavior patterns. However, [45] explains how a high bounce rate often indicates that the website content did not meet the visitor's expectations or that there are technical issues preventing further navigation. Therefore, 17% represents strong performance.

The bounce rate performance may have been influenced by the composition of referral traffic and existing brand familiarity, in addition to the UI modernization. The

Table 13: Cycle 1: User Acquisition and Engagement Metrics.

Metric	Value
Unique Users	844
Total Sessions	~1 250
Session Duration	5 min 15 sec
Bounce Rate	17%
Pages per Session	1.2
Peak Daily Sessions	117

predominance of visitors arriving through brand awareness channels (organic search following email outreach, professional network referrals) suggests that users arrived with specific intent and prior knowledge of the company’s services. This pre-qualified traffic naturally exhibits higher engagement levels compared to cold traffic acquisition strategies, explaining the sustained attention and low immediate exit rates observed across the measurement period.

Table 14: Cycle 1: Traffic Sources Distribution.

Traffic Source	Sessions	Percentage
Google (Total)	339	27.1%
LinkedIn (Total)	256	20.5%
Pampam.city	27	2.2%
Instagram	13	1.0%
Bing	9	0.7%
Facebook	7	0.6%
Other Sources	599	47.9%
Total	1 250	100.0%

Referral traffic analysis indicated Google as the primary traffic source, generating 332 direct referrals from the main search platform and an additional 7 referrals from the Italian domain (Google.it), collectively contributing 339 sessions and representing the dominant organic search acquisition channel (Table 14). LinkedIn emerged as the second-largest traffic source, providing 214 direct referrals and an additional 42 referrals through the mobile application interface, totaling 256 sessions from the professional networking platform. These numbers do not support H4 (Multi-Channel Traffic Integration), as most traffic did not originate from LinkedIn.

The unexpected dominance of Google traffic over LinkedIn referrals can be may be associated with two primary factors. First, the company’s ongoing cold emailing outreach strategy likely created brand awareness that subsequently drove organic search behavior, with recipients searching for the company name rather than clicking through social media links. Second, the LinkedIn promotion strategy may have been insufficiently exploited during the measurement period, with limited content frequency and engagement tactics failing to maximize the platform’s referral potential for B2B audiences.

Additional referral sources included the regional platform Pampam.city (27 sessions), internal site navigation (18 sessions), Instagram’s link shortener service (13 sessions), Bing search engine (9 sessions), Facebook (7 sessions), and the talent platform Nova Talent (4 sessions).

Table 15: Cycle 1: Behavioral and Temporal Metrics.

Metric	Value	Date/Context
Total Sessions	1 250	Full measurement period
Average Pages per Session	1.2	Full measurement period
Peak Pages per Session	1.97	April 30, 2025
Minimum Pages per Session	1.03	May 23, 2025
Peak Daily Sessions	117	May 20, 2025
Minimum Daily Sessions	8	May 11, 2025

The website recorded 1250 total sessions generating around 1500 page views, resulting in an average of 1.2 pages per session (Table 15). Session depth varied, peaking at 1.97 pages per session on April 30, 2025, and reaching a minimum of 1.03 pages per session on May 23, 2025, suggesting fluctuating user engagement levels correlating with content updates or promotional activities. Session analysis revealed significant daily variation in user engagement, with peak activity reaching 117 unique sessions on May 20th, 2025, coinciding with social media promotional activities, while minimum engagement of 8 sessions occurred on May 11th, corresponding to typical Sunday traffic patterns.

Geographic analysis (Table 16) revealed a strong Italian user base (682 users, representing 80.8% of total traffic), with international users primarily originating from the United States (45 users), Germany (17 users), Spain (15 users), and Switzerland (16 users).

The concentration of Italian users aligns with the company’s strategic market focus and existing network effects. This geographic distribution was anticipated given the organization’s deliberate concentration on the Italian market, existing client relationships, and Italian-language content strategy. The limited international traffic reflects the company’s current strategic decision to establish strong domestic market presence before considering geographic expansion, rather than representing a limitation of the digital marketing approach.

Device preference analysis showed a slight desktop predominance, with 482 users (57%) accessing the website via desktop devices and 363 users (43%) utilizing mobile devices.

Conversion tracking (Table 17) focused on meaningful user actions across different website sections. The primary conversion mechanism involved form submissions through "SEND MESSAGE" call-to-action buttons, which generated two successful contacts through the general contact page and two additional contacts through the Levels OS-specific page. Secondary conversion tracking monitored scheduling appointment clicks, recording five clicks on the "Do you prefer calling us? Book a call with [Name]" link, though none resulted in completed bookings. The Levels OG section recorded

Table 16: Cycle 1: User Demographics.

Category	Segment	Count (%)
Geography	Italy	682 (80.8%)
	United States	45 (5.3%)
	Germany	17 (2.0%)
	Switzerland	16 (1.9%)
	Spain	15 (1.8%)
Device	Desktop	482 (57%)
	Mobile	363 (43%)

zero form submissions. Overall, the website generated inquiries from four potential clients and one employment candidate during the measurement period. Therefore, H2 (Conversion Funnel Optimization) was supported, generating 4 qualified leads, exceeding the target of 3.

Table 17: Cycle 1: Conversion Metrics.

Conversion Type	Count	Counts as qualified lead	Source
General Contact Forms	2	Yes	Main contact page
LEVELS OS Forms	2	Yes	Product-specific page
Call Booking Clicks	5	No	No completed bookings
Employment Inquiries	1	No	Career interest
Total Qualified Leads	4	-	Exceeds H2 target

Landing page performance analysis (Table 18) demonstrated clear user preference hierarchies, with the homepage (www.levelstech.it) receiving 912 unique sessions, followed by the Levels OG page (114 sessions) and Levels OS page (70 sessions). This traffic distribution pattern suggests effective information architecture and user navigation flow.

Table 18: Cycle 1: Landing Page Performance.

Landing Page	Sessions	Percentage
Homepage (www.levelstech.it)	912	73.0%
LEVELS OG Page	114	9.1%
LEVELS OS Page	70	5.6%
Other Pages	154	12.3%

LinkedIn performance (Table 19) demonstrated strong visitor engagement despite reduced content reach, with 12254 impressions (-21.9% from past 30 days) generating 183 reactions (+2.8%). Profile visits increased significantly to 961 unique visitors (+50.6%) and 1968 page views (+38.4%), peaking on May 20, 2025 with 577 total views (290 mobile, 287 desktop). Visitor demographics revealed targeted professional engagement, with Engineering professionals comprising 21.2% (418 visitors), Business

Development 15.2% (299 visitors), and Sales 5.7% (112 visitors), indicating successful reach within relevant B2B decision-maker segments.

Table 19: Cycle 1: LinkedIn Performance Metrics.

LinkedIn Metric	Value	Change
Impressions	12 254	-21.9%
Reactions	183	+2.8%
Profile Visits	961	+50.6%
Page Views	1 968	+38.4%
Peak Day Views	577	May 20, 2025

The data collected during the first AR cycle met performance expectations as evaluated by company stakeholders. A bounce rate of 17% was registered, which is well below the target maximum of 50%. However, because the promotional campaign, referral traffic composition, and existing brand familiarity were all active influences during the same period, it is not possible to isolate the effect of the UI modernization alone. As a result, Hypothesis 1 (User Interface Modernization) remains inconclusive.

In conclusion, data collected with PostHog provided valuable insights that would have not been discovered without analytics tracking, such as more visits on the "about" page rather than the "portfolio" page, long time spent on the carousel of images in the homepage, low visits on the products pages. Therefore, H3 (Analytics-Driven Decision Making) is supported.

4.4.5 Phase 5: Learning

The learning phase involved systematic reflection on intervention outcomes and identification of insights for both theoretical understanding and practical application. Several key learnings emerged from this first cycle that will inform subsequent iterations.

The rapid development approach using AI-assisted coding tools demonstrated viability in the startup context, enabling quick market entry and early user feedback collection. This supports the applicability of the Build-Measure-Learn framework for early-stage website optimization initiatives. The decision to prioritize functional implementation over detailed design system development was supported by achieved user acquisition and engagement metrics.

Analytics integration from the project initiation proved crucial for evidence-based evaluation and decision-making. The comprehensive tracking implementation enabled detailed user behavior analysis that would not have been possible with retroactive analytics addition ("PostHog is showing us patterns and features we never expected. We can even see user recordings and observe how they navigate through our website!", company's co-founder).

The successful application of CAR methodology in this context demonstrates its viability for bridging academic rigor with practical startup requirements. The integration of UI/UX design principles with systematic measurement approaches provided a

structured framework for intervention design and evaluation while maintaining the flexibility required in dynamic organizational environments.

The geographic analysis revealed untapped international market potential that could be addressed through targeted content localization strategies. However, from internal discussions with the co-founders, this is not of the company interest to be explored at the moment, as the focus remains on the Italian market.

However, the learning process also identified areas requiring improvement in subsequent cycles. A few problems emerged from both the evaluation of the analytics and the extra activity of watching 10 offline recordings of users using the website, and observing patterns.

First, it was noticed that, given the lack of a dedicated designer in the company, it was necessary to add qualitative data to the current data collected, such as with interviews or polls. Recordings showed ways of utilizing the website that were not expected, such as low engagement with the "Portfolio" section, which was considered to be the most visited one.

Second, during the collection of the analytics after one month, it was clear that the information on the website, particularly when trying to explain the different services and products the company offers, were too much.

Finally, LinkedIn turned out to be a good referral source, but the lack of marketing on the platform could limit visits.

4.5 Hypotheses after Cycle 1

H5 (Message Clarity and Value Proposition): Structured user interviews will reveal specific communication gaps that quantitative analytics alone cannot identify, leading to actionable insights for improving message clarity.

H6 (Navigation Optimization and Information Architecture): Modification of navigation from "Portfolio" to "Our Projects" will increase visits to the projects section by at least 25%. H5 and H6 contribute to investigate RQ1 (UI/UX Design Improvements).

H7a (Multi-Channel Traffic Integration): Migration of LEVELS OS to a dedicated website will improve conversion rates for both sites by reducing cognitive overload while maintaining referral traffic between properties.

H7b (Offline-to-Online Marketing Integration): The coordinated launch campaign for LEVELS OS (exhibition presence, printed materials, QR codes) will generate measurable cross-channel attribution and demonstrate effectiveness of integrated offline-to-online marketing strategies.

4.6 Interviews and Updated Navigation Organization

The second AR cycle incorporated a mixed-methods approach, combining qualitative user research with targeted website modifications to address the conversion optimization challenges identified in Cycle 1. This cycle spanned from May 30 - June 30 2025, focusing on deeper user understanding through structured interviews while

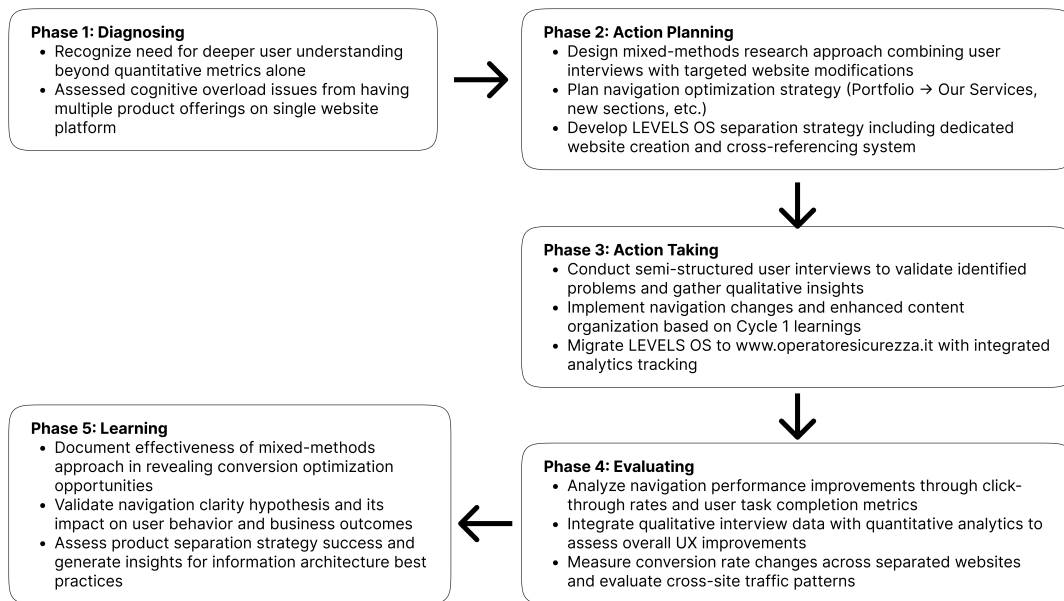


Figure 4: Overview of the 5 steps of the 2nd AR Cycle (May 30 - Jun 30 2025).

simultaneously implementing navigation and information architecture improvements based on emerging insights, as shown in Figure 4.

4.6.1 Phase 1: Diagnosing

The diagnostic phase of Cycle 2 was initiated following the quantitative analysis from Cycle 1, which revealed successful user acquisition (844 unique users) but limited conversion outcomes (four qualified leads). While analytics data indicated positive engagement metrics, including a 17% bounce rate and average session duration of 5 minutes 15 seconds, these quantitative indicators alone could not explain why the relatively high engagement failed to translate into proportional conversion rates.

The need for qualitative investigation emerged from this performance gap. Quantitative metrics suggested users were engaging with the content but not converting at expected rates, indicating potential barriers in communication clarity, value proposition understanding, or trust establishment that required deeper investigation through direct user feedback.

Additionally, preliminary informal feedback suggested cognitive overload from presenting multiple product offerings (consulting services, LEVELS OS, LEVELS OG) on a single platform. This observation warranted systematic investigation to determine whether product separation would enhance conversion performance for both offerings.

4.6.2 Phase 2: Action Planning

The qualitative research component was designed following established HCI interview methodology principles, with a focus on understanding user perceptions of the

company's value proposition, navigation clarity, and trust factors.

Interview protocol (Table 2) development emphasized open-ended questioning to elicit unbiased user interpretations of the website's purpose and offerings. The protocol included structured tasks (website exploration) followed by semi-structured questioning about comprehension, clarity, and decision-making processes. Participant recruitment targeted both technical and non-technical users to ensure diverse perspectives on the AI consulting services presented.

Concurrent with interview planning, website modification strategies were developed based on preliminary insights from Cycle 1. These included navigation label optimization (changing "Portfolio" to "Our Projects"), content reorganization to improve information hierarchy, and planning for LEVELS OS migration to a dedicated domain. These modifications were designed to be implemented iteratively as interview insights emerged.

The second cycle's action planning explicitly applied the mixed-methods approach advocated in CAR literature, combining quantitative analytics with qualitative user research to address the conversion optimization gap identified in Cycle 1. Following [8]'s emphasis on using instrumental theories to support research activities, structured interview methodology was selected to complement the quantitative data collection, providing the contextual understanding necessary for evidence-based decision making.

The planning phase integrated CE principles by treating each identified improvement area (message clarity, navigation optimization, product separation) as testable hypotheses requiring systematic validation. The approach aligned with the RIGHT model's emphasis on hypothesis-driven development [32], where product decisions are guided by experimental validation rather than intuition.

The cyclical process model guided the integration of qualitative insights with quantitative validation, ensuring that interview findings would inform specific website modifications that could be empirically evaluated. This approach embodied CAR's Change Through Action principle by ensuring that research activities would result in concrete organizational improvements while contributing to academic understanding of startup optimization challenges.

4.6.3 Phase 3: Action Taking

Eight semi-structured interviews were conducted between June 18 and June 23, 2025, with participants representing diverse backgrounds in terms of technical expertise (Table 20). Participants were recruited by convenience sample and requirements specified Italian as their native language. Sessions were conducted both remotely via video conferencing and in-person, lasting between 15-30 minutes each. The interview process followed ethical research guidelines, with informed consent (Figure A1) obtained from all participants and no audio or video recording conducted to ensure participant comfort and candid feedback.

The interview protocol (Table 2) consisted of initial free exploration of the website, followed by targeted questions (Appendix B), and open-ended discussion prompts. Observational notes were taken during each session.

The navigation item "Portfolio" was renamed to "I Nostri Progetti" (Our Projects).

Table 20: Cycle 2: Interview Participant Demographics and Background.

Participant	Technical Background	Interview Format
P1	Technical	Remote
P2	Non-technical	In-person
P3	Technical	Remote
P4	Non-technical	Remote
P5	Technical	In-person
P6	Non-technical	Remote
P7	Technical	Remote
P8	Non-technical	In-person
Total	4 Technical, 4 Non-technical	5 Remote, 3 In-person

Along with that, four projects descriptions were added at the bottom of the landing page, to persuade users clicking on "Read more" or "See more". Additionally, a big header was added under the "Partner" section, stating "We transform the way companies work with documents, simplifying bureaucracy processes", as it was observed that users spent some time reading about the partners.

To promote and focus more on the company's main product (LEVELS OS), and improve SEO for people browsing, for example, "AI software for site construction safety" or "software for itp analysis", a new dedicated website was created (www.operatoresicurezza.it). The content of LEVELS OS was then moved to the new website and, to maintain integrity with the previous website, the CTA to navigate to the product remained the same, with the only difference that the click redirects the user to the new website. To offer a more immersive experience for the new website, demo videos were added, the layout of the page was slightly changed, and the content of the website was designed to focus entirely on the product and not on the company. This version of the website was the version that participants of the interviews used.

Finally, from June 4 - June 6 2025, two members of the company attended the "We Make Future" fair in Bologna (Italy), an international fair on artificial intelligence, technology, and digital innovation, promoting the company. For the occasion, 50 brochures, 1 roll up, and 40 business cards were designed and printed, as shown in Figure 5.

4.6.4 Phase 4: Evaluating

The evaluation phase encompassed systematic analysis of collected data during the second measurement period (May 30 - June 30, 2025). Overall, two of the four hypotheses were supported and one partially supported, while there were not enough data to investigate H6 deeper, as shown in Table 21.

The evaluation of the interviews employed Braun and Clarke's six-phase thematic analysis framework [46], ensuring systematic and rigorous pattern identification within the interview dataset. This methodological approach was selected for its established validity in qualitative HCI research and its flexibility in identifying both semantic and latent themes.



Figure 5: Printed material for the "We Make Future" fair in Bologna (Italy), June 4 - June 6 2025.

Table 21: Cycle 2: Hypothesis Validation Results.

Hypothesis	Target	Supported
H5: Message Clarity	Identify communication gaps	Yes
H6: Navigation Optimization	25% increase in project visits	Inconclusive
H7a: Product Separation	Improved conversion rates	Partially
H7b: Offline-to-Online Integration	Measurable attribution	Yes

Phase 1 (Familiarization) involved repeated reading of interview notes and translation from Italian to English while preserving semantic nuance. This immersion process revealed significant variation in comprehension levels between technically-oriented and non-technical participants, establishing an initial understanding of the data's complexity.

Phase 2 (Initial Coding) generated systematic codes across all eight interviews, identifying discrete concepts relevant to website comprehension and user experience. Notable codes included confusion about business model (software vs. consulting), terminology barriers ("operatori digitali"), and requests for tangible demonstrations such as demo videos. The latter was requested even though the LEVELS OS website included video demos, but during the interviews only one participant navigated to the page where they were placed. The term "operatori digitali" ("digital operators" in English) is a term coined by the company to describe AI agents (autonomous software entities designed to perform tasks, make decisions, and interact with their environment independently [47]).

Phase 3 (Theme Development) involved collating codes into potential themes through pattern recognition and conceptual grouping. Related codes such as technical

jargon critiques and terminology confusion were grouped under broader communication themes, while navigation and content hierarchy issues formed structural themes.

Phase 4 (Theme Review) refined the initial themes through two-level validation: first ensuring internal coherence within each theme’s data extracts, then validating themes against the complete dataset. This process resulted in consolidation from ten initial themes to four robust, distinct themes that comprehensively represented user feedback.

Phases 5 and 6 (Definition and Reporting) produced the final thematic structure with clear definitions and supporting evidence for each theme, as detailed in the following findings.

Four major themes emerged from the analysis, each providing actionable insights for conversion optimization (Table 22).

Table 22: Cycle 2: Thematic Analysis - Major Themes and Supporting Evidence.

Theme	Key Issues	Representative Quote/Observation
Ambiguity in Core Offering	Software vs. consulting confusion	"Initially perceived as Copilot but concluded it was more consulting than SaaS"
Jargon as Barrier	Technical terminology problems	"Operatori digitali" interpreted as human agents rather than AI components
Flawed Information Hierarchy	Critical content positioned poorly	"Operators section helpful when found, but placed too low on page"
Need for Tangibility	Demand for concrete demonstrations	Explicit requests for "demos", "videos", "simple examples"

Theme 1: Ambiguity in the Core Offering emerged as the dominant barrier to conversion. Participants consistently struggled to determine whether the company offered ready-made software, customizable tools, or consulting services. This fundamental ambiguity prevented potential clients from self-qualifying and understanding the relevance of the offering to their specific needs. The confusion was exemplified by one participant who initially perceived it as "Copilot" but later concluded it was "more consulting than SaaS." This theme directly validated H5 regarding message clarity deficiencies.

Theme 2: Jargon as a Barrier to Understanding identified specific terminology that alienated users, particularly non-technical audiences. The term "operatori digitali" (digital operators) was universally problematic, with multiple participants interpreting it as referring to human agents rather than AI components. Similarly, "burocrazia" (bureaucracy) was perceived as vague and potentially negative. These linguistic barriers created immediate comprehension obstacles that likely contributed to the low conversion rates observed in Cycle 1.

Theme 3: Flawed Information Hierarchy revealed structural issues preventing users from accessing clarifying information efficiently. Critical explanatory content,

particularly the "operators" section that helped users understand the offering, was positioned too low on the page. Participants reported feeling overwhelmed by text volume and struggled to locate key information that would have facilitated understanding. This theme provided evidence supporting H6 regarding navigation and information architecture optimization needs.

Theme 4: The Need for Tangibility expressed users' desire for concrete demonstrations of the service in action. Abstract descriptions of AI capabilities failed to convey practical value, with participants explicitly requesting "demos", "videos", or "simple examples" to understand application scenarios. This finding suggested that theoretical or technical descriptions alone were insufficient for building trust and understanding in complex AI services and that the videos of LEVELS OS were not easy to find.

The interviews proved to be effective and therefore support H5 (Message Clarity and Value Proposition), providing more insights than initially expected and highlighted crucial pain-points that were not identified before.

After the rename of the navigation item from "Portfolio" to "Our Projects", and the addition of projects and CTAs in the landing page, the projects pages were eventually visited 19 times with the new version of the website (3% considering a total of 627 visitors), compared to the 27 times (2,8% on a total of 844 visitors) measured during the 1st AR cycle (Table 23). However, the number of unique users during the 2nd AR cycle dropped from 844 to 627. Therefore, these data are not enough to support H6 (Navigation Optimization and Information Architecture), which expected an increase of 25% of the visits.

The failure of navigation optimization to improve project section visits may be associated with fundamental message clarity issues rather than interface design problems. The qualitative interviews revealed that users struggled with basic comprehension of the company's value proposition, suggesting that navigation improvements were premature when core communication barriers remained unresolved. Additionally, the addition of more content and CTAs may have inadvertently increased cognitive load, creating a paradoxical effect where additional information decreased rather than improved user experience.

Table 23: Cycle 2: Projects Section Performance Comparison (Cycle 1 vs Cycle 2).

Metric	Cycle 1 ("Portfolio")	Cycle 2 ("Our Projects")	Change
Projects Page Visits	27	19	-29.6%
Total Unique Users	844	627	-25.7%

LinkedIn performance during the second measurement period showed increased content engagement with 17571 impressions (+30.1% from the previous 30 days) and 273 reactions (+34.5%), but reduced profile traffic with 669 unique visitors (-33.4%) and 1666 page views (-19.7%), as reported in Table 24. Peak engagement occurred on June 16, 2025 with 182 total views (159 mobile, 23 desktop), notably lower than the previous cycle's peak. Visitor demographics shifted toward business-focused professionals, with Business Development leading at 19% (317 visitors), followed by

Engineering at 10.8% (180 visitors) and Product Management at 8.8% (147 visitors), suggesting evolving audience composition despite overall decreased profile visitation.

Table 24: Cycle 2: LinkedIn Performance Metrics Comparison.

Metric	Cycle 1	Cycle 2	Change
Impressions	12 254	17 571	+30.1%
Reactions	183	273	+34.5%
Profile Visits	961	669	-33.4%
Page Views	1 968	1 666	-19.7%
Peak Day Views	577 (May 20)	182 (June 16)	-68.5%
Top Visitor Profession	Engineering (21.2%)	Business Dev (19%)	Shifted

Lead generation analysis showed maintained conversion volume of the LEVELS OS product following product separation, with two qualified contacts recorded during the 2nd evaluation period, equal to Cycle 1. Importantly, this consistency was achieved across two distinct conversion funnels rather than a single mixed-offering pathway, indicating maintained qualification efficiency where potential clients can more readily identify their specific needs. The maintenance of conversion rates while expanding to dual-site architecture supports the cognitive load reduction hypothesis, indicating that clearer value proposition communication offsets any potential traffic dilution effects.

The migration of LEVELS OS to the dedicated domain *operatorosicurezza.it* on June 1, 2025, generated indeed measurable outcomes supporting the product separation strategy mentioned in H7a (Table 25). Cross-site referral tracking revealed 625 unique sessions directed from the main consulting website to the specialized product site during the evaluation period, indicating effective user navigation between the separated digital properties. This referral volume suggests that users encountering the LEVELS OS offering on the main site were effectively guided to the dedicated product experience without friction in the user journey. Engagement quality analysis revealed remarkable consistency between the separated sites, with the dedicated LEVELS OS website recording an average session duration of 5 minutes 13 seconds compared to 5 minutes 15 seconds on the main consulting site during the previous measurement period. This near-identical engagement metric suggests that product separation maintained user interest and content relevance while eliminating the cognitive overload associated with mixed service offerings. However, H7a remains partially unsupported since the new website generated only two qualified leads for the LEVELS OS product, which equal to the number of contacts for that product received during the 1st AR cycle.

The maintenance of identical lead generation numbers across separated product sites likely reflects external market factors rather than cognitive load reduction effectiveness. Potential explanations include reduced outreach activity during the measurement period, seasonal decision-making delays as summer approached, or the presence of non-target visitors driven by promotional activities rather than genuine product interest.

In regard to H7b, it is possible to confirm that the coordinated offline-to-online marketing strategy demonstrated clear attribution success during the exhibition period

Table 25: Cycle 2: LEVELS OS Dedicated Website Performance Metrics.

Metric	Value	Comparison to Main Site
Launch Date	June 1, 2025	-
Average Session Duration	5 min 13 sec	5 min 15 sec (main site)
Qualified Leads Generated	2	2 (main site)
Domain	operatoresicurezza.it	levelstech.it
Content Focus	Product-specific	Consulting services
Demo Videos Added	Yes	No

(June 4-6, 2025), as shown in Table 26. Traffic analysis revealed a significant engagement peak on June 5, 2025, with 51 unique sessions recorded, representing the highest single-day traffic volume during the measurement period. This peak coincided directly with the company’s exhibition presence, supporting H7b’s assertion. The exhibition materials, including QR codes, printed collateral, and live demonstrations, generated measurable online traffic from offline engagement.

The exhibition and social media promotion may have generated curiosity-driven traffic that engaged with content but lacked purchasing intent, diluting the conversion potential of the separated product experiences despite improved information architecture.

The immediate traffic spike following the exhibition demonstrates the effectiveness of integrated offline-to-online marketing strategies. The combination of hands-on product demonstrations, direct personal interaction, and actionable QR code materials created multiple touchpoints that facilitated immediate digital engagement. Unlike passive promotional activities, the exhibition format enabled trust-building through face-to-face interaction and tangible product experience, which research suggests significantly increases subsequent online engagement rates in B2B contexts. The QR code integration provided frictionless transition from offline interest to online exploration, capturing engagement momentum while visitor motivation remained high.

Table 26: Cycle 2: Offline-to-Online Marketing Performance (We Make Future Exhibition).

Metric	Value	Date
Exhibition Dates	June 4-6, 2025	Bologna, Italy
Peak Traffic Day	51 unique sessions	June 5, 2025
Materials Distributed	50 brochures, 40 cards, 1 roll-up	-
QR Code Scans	Included in peak traffic	-

4.6.5 Phase 5: Learning

The integration of qualitative user research with quantitative analytics in Cycle 2 generated critical insights validating the mixed-methods approach for conversion

optimization in complex technical domains. The thematic analysis revealed communication and structural barriers that were invisible in quantitative metrics alone, demonstrating the complementary value of qualitative investigation in understanding the "why" behind user behavior patterns.

The identification of terminology as a significant barrier highlighted the importance of user-centered language in technical product communication. The finding that even technically-oriented users struggled with internal jargon suggests that startups often develop insider language that inadvertently excludes potential clients.

Information architecture emerged as equally critical to conversion as visual design, with users requiring clear narrative flows to understand complex offerings. The success of the "operators" section when users found it, contrasted with its poor placement, illustrated how structural decisions can undermine otherwise effective content.

The demand for tangible demonstrations, despite the four additional CTAs and the demo videos in the LEVELS OS page, reflects broader challenges in communicating AI value propositions, where abstract capability descriptions fail to connect with concrete user needs.

Despite renaming "Portfolio" to "Our Projects" to be more descriptive and intuitive [48], and adding project previews with CTAs on the landing page to persuade visitors to visit the projects page, the projects section experienced decreased visitation (19 visits compared to 27 in Cycle 1). However, this decrease occurred alongside an overall traffic reduction from 844 to 627 unique users, suggesting that external factors such as reduced promotional activity or seasonal variations may have influenced the results more significantly than the navigation changes themselves. This finding emphasizes the importance of controlling for external variables when evaluating interface modifications and suggests that navigation optimization effects may be more subtle than anticipated, requiring longer measurement periods or larger sample sizes to detect statistical significance.

Comparing the two LinkedIn measurement periods reveals contrasting performance trends in content engagement versus profile visitation. While content reach and engagement improved significantly in the second period, with notable increases in both impressions and reactions, profile traffic declined substantially across unique visitors and page views. The peak engagement days also differed markedly, with May showing much stronger profile visitation than June, indicating reduced conversion from content visibility to profile exploration. The audience composition shifted from engineering-heavy participation in the first period to business development-focused engagement in the second, suggesting evolving content resonance with different professional segments despite overall decreased profile engagement.

After the product separation, a successful maintenance of engagement quality (5 minutes 13 seconds on the dedicated site versus 5 minutes 15 seconds on the main site) while handling 625 cross-site referrals demonstrated that users could navigate between separated properties without friction. However, the identical lead generation numbers (two qualified contacts from each site) suggest that separation alone is insufficient to increase overall conversion volume. Instead, the strategy appears to have successfully redistributed existing conversion potential across more targeted funnels, potentially improving lead quality by enabling better self-qualification. The exhibition-driven

traffic spike (51 sessions on June 5, 2025) confirmed the effectiveness of omnichannel marketing approaches, demonstrating that offline presence can generate measurable online engagement when properly coordinated with digital infrastructure.

5 Discussion

5.1 The Effectiveness of Integrating CAR with CE for Website Optimization in Resource-Constrained Startups

This section addresses RQ1: *How can the application of Canonical Action Research methodology combined with Continuous Experimentation principles enable effective website optimization in resource-constrained AI startup environments?*

The evidence from this study reveals a paradox of surface-level success masking deeper structural barriers in UI/UX design improvements for early-stage AI startups. The redesign of the website according to contemporary design principles coincided with strong engagement metrics, achieving a 17% bounce rate and an average session duration of 5 minutes 15 seconds. However, while engagement improved, it remains inconclusive whether we can attribute this effect solely to the redesign of the website, given concurrent factors such as promotional campaigns and referral traffic composition. Moreover, these descriptive gains did not translate proportionally into conversion outcomes.

A study conducted by Nalis [49], for instance, shows in a similar way how enhancements in UI/UX, such as interface design changes, can improve certain aspects like serendipity in books recommendations systems but may not significantly increase user trust or overall satisfaction, which are crucial for conversions.

This paradox manifests in two critical ways. First, aesthetic modernization creates engagement without comprehension. The initial template-based redesign with Lovable, created following the UI/UX principles described in Section 2.2, successfully retained user attention, evidenced by sustained session durations, yet qualitative analysis revealed that users remained fundamentally confused about the company's value proposition. As one participant noted: "Initially perceived as Copilot but concluded it was more consulting than SaaS," illustrating how visual appeal cannot compensate for conceptual clarity deficits. Involving users in the development of value propositions could have helped ensure that the offerings were aligned with their needs and expectations, reducing confusion [50],

Second, conversion barriers operate at the semantic rather than syntactic level. The consistent lead generation across both cycles (2 leads for LEVELS OS in both Cycle 1 and Cycle 2) suggests that conversion challenges stem from communication architecture rather than interaction design. Users who successfully converted likely possessed prior context or domain expertise that enabled them to navigate conceptual barriers regardless of interface design quality.

The implications for early-stage AI startups are profound: UI/UX improvements are necessary but insufficient conditions for conversion optimization. The data suggests a hierarchical relationship where message clarity and information architecture must be resolved before visual design improvements can achieve their full potential. This finding contradicts the common startup practice of prioritizing visual redesigns over content strategy, suggesting that resources should be allocated to communication clarity before interface aesthetics.

5.2 The Hierarchy of Design and Content Elements in Driving Website Conversions

This section addresses RQ2: *Which design elements and content strategies, when evaluated through Continuous Experimentation principles, demonstrate the strongest measurable impact on lead qualification and conversion rates in resource-constrained AI startup environments?*

The hierarchy validation emerges clearly through contrasting outcomes between research cycles. Cycle 1's successful visual design implementation coincided with strong engagement metrics (17% bounce rate, 844 unique users, 5 minutes 15 seconds average session duration) yet only modest conversion outcomes were generated (4 qualified leads). This performance gap persisted despite implementing contemporary UI/UX principles and strategic call-to-action placement, indicating that aesthetic improvements alone cannot address fundamental communication barriers. When creating visual design elements, there is a balance to be struck; excessive visual intensity can lead to negative user responses and decreased conversion rates, while too little can fail to capture user interest [51]. While interactivity can enhance user involvement and positive affect, it does not necessarily improve message comprehension, memory, or knowledge gain. In general, it is important to consider that high levels of interactivity might not benefit users' cognitive processes, especially on informational websites [52]. The subsequent Cycle 2 qualitative investigation revealed the underlying cause: All the participants struggled with basic value proposition comprehension, demonstrating that users remained fundamentally confused about service offerings regardless of interface quality.

The semantic clarity primacy was further validated through specific intervention failures and successes across both cycles. Navigation optimization in Cycle 2 (H6) demonstrated this principle directly, where theoretically sound improvements (renaming "Portfolio" to "Our Projects" and adding project previews and additional call-to-action elements) coincided with a slight increase in visits to the project section (2,8% to 3%). The product separation strategy (H7a) successfully maintained identical engagement quality (5 minutes 13 seconds vs. 5 minutes 15 seconds) while handling 625 cross-site referrals, indicating that architectural clarity enables user navigation without friction. The universal demand for tangible demonstrations identified in Cycle 2 interviews directly addressed the conversion gap observed in Cycle 1, where sustained user attention failed to translate into purchasing intent due to abstract capability descriptions that prevented users from understanding practical value propositions.

By reviewing existing literature, content architecture elements, such as usability, system quality, and information quality, have been shown to significantly affect conversion rates on e-commerce websites. These elements ensure that users can easily navigate the site, find the information they need, and trust the quality of the content, which in turn encourages them to complete desired actions like making a purchase or registering for an account [53]. Additionally, the structure and organization of information, such as clear calls to action and optimized checkout processes, are crucial for improving conversion rates [54].

Visual design elements, including aesthetics, color, imagery, and layout, also play

a critical role in influencing user behavior and conversion rates. Effective visual design can guide users' attention, evoke emotions, and create a professional and trustworthy appearance, all of which can enhance user engagement and satisfaction [55].

However, although visual aesthetics, particularly classical aesthetics (simplicity, clarity, orderliness), have a stronger impact on perceived credibility and trust than expressive aesthetics (complexity, richness, novelty) [56], the research suggests that content architecture elements have a greater conversion impact than visual design elements. This challenges the conventional prioritization of aesthetic improvements in startup website optimization. The evidence suggests a clear hierarchy of influence: semantic clarity > information architecture > visual design.

Semantic clarity emerges as the primary conversion determinant. The thematic analysis identified "Ambiguity in Core Offering" as the dominant barrier, with all the interview participants struggling to categorize the company's services. This semantic confusion created a foundational barrier that prevented user self-qualification regardless of interface quality. The terminology analysis revealed that even small linguistic choices, such as "operatori digitali" being interpreted as human agents rather than AI components, created immediate comprehension failures that no amount of visual polish could overcome.

Information architecture demonstrates measurable impact through strategic positioning. The qualitative data revealed that when users encountered the explanatory "operators" section, comprehension improved substantially. However, this content was positioned too low on the page, creating a discoverability problem. The successful maintenance of identical session durations (5 minutes 15 seconds vs. 5 minutes 13 seconds) across separated product sites demonstrates that architectural clarity can maintain engagement quality while reducing cognitive load by removing any text and page that was not related to the product.

Visual design elements show limited independent conversion impact. Despite implementing contemporary design principles and achieving strong engagement metrics, conversion rates remained modest.

Tangibility requirements reveal content-specific conversion needs in AI contexts. The universal demand for "demos," "videos," and "simple examples" across all interview participants suggests that abstract capability descriptions are insufficient for AI service communication. This finding suggests that conversion optimization in complex technical domains requires demonstration-based content strategies rather than descriptive approaches.

The research identifies and suggests a conversion hierarchy model for early-stage AI startups (Figure 6): (1) Semantic clarity (value proposition understanding), (2) Information architecture (strategic content positioning), (3) Tangible demonstrations (proof of capability), and (4) Visual design (aesthetic engagement). This hierarchy suggests that startups should address elements in this order to maximize conversion impact per unit of resource investment.

Literature suggests that the relationship between website complexity and user satisfaction can vary based on user goals. For goal-directed users, higher complexity tends to reduce satisfaction, while for experiential users, the relationship follows an inverted-U shape, meaning moderate complexity can enhance satisfaction but too

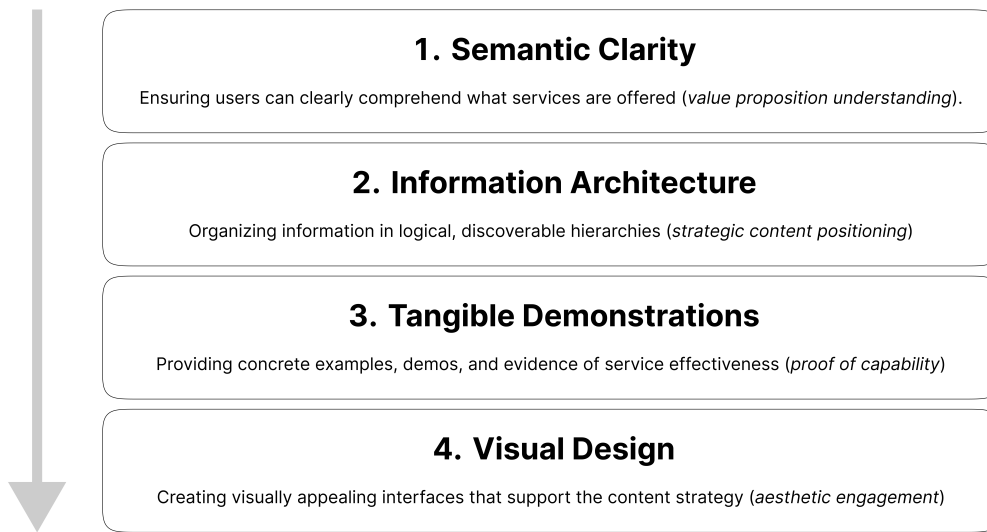


Figure 6: Proposed Conversion Hierarchy Model for Early-Stage AI Startups.

much complexity can be detrimental [57]. The data reveals that traditional conversion optimization approaches may be inappropriate for complex technical services. The maintenance of lead generation after product separation (H7a), which is likely to have reduced cognitive load, suggests that conversion outcomes were likely influenced more by users being able to quickly determine whether the offering was relevant to them than by the presence of persuasive design elements. This suggests that for AI startups, optimizing clarity and helping users self-qualify may be more effective than focusing solely on traditional funnel-based persuasion tactics.

5.3 Social Media as Brand Awareness Amplifier: Understanding Indirect Marketing Effects on Lead Generation

This section addresses RQ3: *How does integrated digital marketing strategy, particularly social media engagement combined with website analytics, influence traffic attribution and lead generation effectiveness in resource-constrained AI startup environments?*

The research reveals a multi-layered influence model where social media marketing operates through indirect brand awareness mechanisms rather than direct conversion channels, with offline-to-online integration demonstrating the strongest measurable impact on generation of qualified traffic (visitors that convert into booking a call).

Other studies have already shown that social media content, such as Instagram posts, significantly affects customer feedback and brand awareness. The indirect effect of social media content through customer feedback is notably stronger than the direct effect [58]. Conversion-oriented campaigns aimed at targeted potential customers can indirectly shape brand awareness by driving branded search activity, suggesting an unacknowledged role in building brand recognition [59].

In this study case, social media functions as a brand awareness amplifier rather than direct conversion channel. While LinkedIn emerged as the second-largest traffic source (256 sessions, 20.5% of total traffic), the predominance of Google traffic (339 sessions, 27.1%) suggests that social media exposure drives subsequent brand search behavior rather than immediate conversion. This indirect influence pattern is critical for early-stage startups because it demonstrates that social media investment should be evaluated on awareness metrics rather than direct attribution models.

Platform-specific engagement patterns reveal audience segmentation effects. The comparison across measurement periods shows contrasting performance: Cycle 1 achieved strong profile engagement (961 unique visitors, +50.6%) while Cycle 2 demonstrated increased content engagement (17571 impressions, +30.1%) but reduced profile visitation (669 unique visitors, -33.4%). This divergence suggests that content visibility does not automatically translate to profile exploration, suggesting that social media marketing must be optimized for specific objectives rather than general "engagement."

Offline-to-online integration provides the strongest attribution that was measured. The exhibition strategy (H7b) generated the clearest evidence of social media marketing effectiveness, with a 51-session traffic spike on June 5, 2025, directly correlating with the "We Make Future" exhibition presence. This omnichannel approach, combining physical presence, printed materials with QR codes, and coordinated social media promotion, created multiple touchpoints that facilitated immediate digital engagement. The success of this integrated approach suggests that social media marketing achieves maximum impact when combined with tangible interaction opportunities rather than operating as a standalone channel.

Audience composition analysis reveals qualification effects. The shift from engineering-heavy participation (21.2%) in Cycle 1 to business development-focused engagement (19%) in Cycle 2 demonstrates that social media marketing can influence audience quality, not just quantity. This finding is particularly relevant for B2B startups where reaching decision-makers is more valuable than general engagement metrics.

The research identifies three distinct social media influence mechanisms (Figure 7): (1) *Awareness Generation* - creating brand familiarity that drives subsequent organic search behavior; (2) *Audience Curation* - attracting specific professional segments relevant to the business model; and (3) *Omnichannel Amplification* - enhancing offline engagement through integrated digital touchpoints.

Most importantly, the data reveals that social media marketing effectiveness depends on integration rather than isolation. The failure of H4 (LinkedIn traffic dominance) combined with the success of H7b (offline-to-online integration) suggests that social media platforms achieve maximum impact when they support broader marketing ecosystems rather than operating as independent traffic sources. This finding challenges the common startup practice of treating social media as a standalone growth channel, instead suggesting that social media investment should be evaluated within integrated marketing strategies.

For early-stage AI startups, this research suggests that social media marketing should be positioned as a brand awareness and qualification tool rather than a direct lead generation mechanism. The optimal approach involves coordinating social media

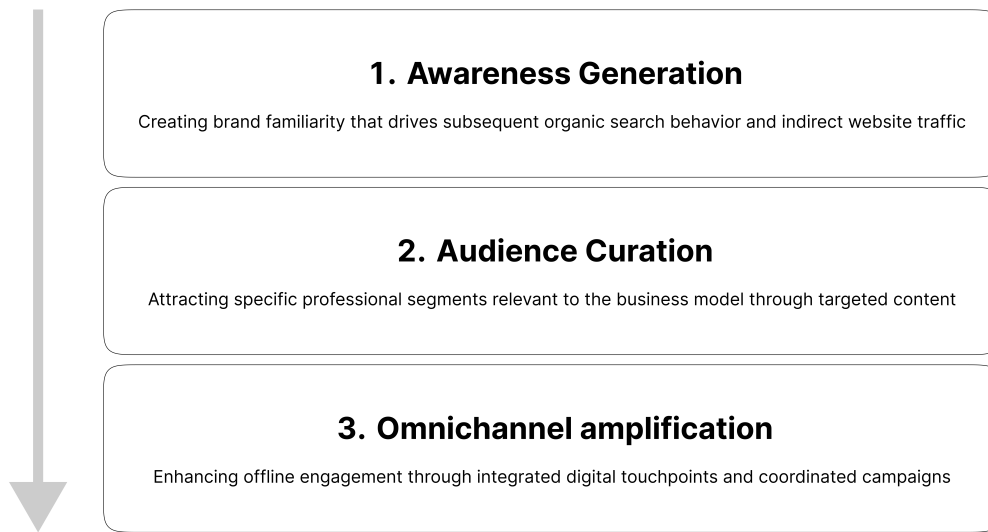


Figure 7: Social Media Influence Mechanism.

presence with other marketing activities, particularly offline engagement opportunities, to create multiple touchpoints that guide prospects through extended consideration cycles typical of B2B technical services.

5.4 Limitations

5.4.1 Methodological and Design Limitations

The single case study design restricts the applicability of findings to other startups or contexts. Results may not be representative of the broader AI consulting industry or different startup stages. The study's focus on one Italian AI consulting startup limits generalizability to other geographic markets, industry sectors, or organizational sizes.

Each action research cycle lasted only one month, which may not capture long-term effects or seasonal variations in user behavior. This limited timeframe is insufficient to observe complete conversion cycles in B2B contexts, where decision-making processes often extend beyond 30 days. The short evaluation periods may not allow for user behavior patterns to stabilize after interventions.

The study did not implement controlled experiments or A/B testing to isolate the effects of specific interventions. Multiple simultaneous changes made it impossible to identify which particular elements drove observed results. This absence of control groups prevents establishing causality between interventions and outcomes.

The application of CAR methodology to technical website optimization may not be optimal compared to more specialized design research approaches. The integration of CE principles was applied in limited scope without full experimental rigor. Some practical decisions lacked strong theoretical grounding from UX/UI design literature.

5.4.2 Data Collection and Measurement Limitations

The study relied primarily on PostHog analytics without validation from alternative tracking methods. Potential technical issues, data gaps, or measurement errors in analytics collection were not systematically addressed. The absence of cross-platform validation limits confidence in the precision of behavioral metrics.

Definitions of "qualified leads" and "conversion" may vary across different contexts and industries. The interpretation of bounce rate and session duration as engagement indicators may not accurately reflect true user interest or satisfaction. LinkedIn metrics may not represent meaningful business outcomes despite indicating platform engagement.

The qualitative component of this research faced several methodological limitations that constrain the credibility and transferability of findings. The study conducted only eight semi-structured interviews, which may not have achieved true data saturation where "you begin to see or hear the same things over and over again, and no new information surfaces as you collect more data" [34]. Additionally, participants were selected through convenience sampling rather than the purposeful maximum variation sampling recommended for enhancing transferability, limiting the applicability of findings to different company sizes, industries, or geographic contexts.

The dual role as both researcher and implementer introduced potential bias in interview conduct and interpretation. The intimate knowledge of the website's intended functionality may have influenced question formulation and thematic analysis. This bias was compounded by the absence of member checks, which the literature identifies as "the single most important way of ruling out the possibility of misinterpreting the meaning of what participants say and do" [60]. The study also lacked investigator triangulation, where multiple researchers independently analyze the same qualitative data and compare findings, limiting the reliability of theme identification.

The interviews were conducted within a narrow timeframe (June 18-23, 2025) and represented only participants' initial impressions, potentially missing how user perceptions evolve over repeated exposure. The predominant focus on Italian users (80.8% of website traffic) and the translation of interviews from Italian to English may have introduced semantic distortion and cultural biases that limit transferability to other markets where business communication styles and trust-building mechanisms differ significantly.

5.4.3 Contextual and External Limitations

External factors such as ongoing cold email campaigns, seasonal market variations, and LinkedIn algorithm changes were not controlled for during the measurement periods. The company's existing outreach activities likely influenced organic search behavior and website traffic patterns, making it difficult to isolate the impact of website improvements alone.

The heavy concentration of Italian users (80.8%) limits the international applicability of findings. Cultural factors in website design preferences and business communication styles were not systematically addressed. Language-specific issues

with Italian terminology may not translate to other markets or languages. However, this limitation does not regard the study itself, as the company's desired target was the Italian population.

Budget limitations affected the scope of possible interventions and the depth of analysis. The reliance on template-based development approaches may not represent optimal design solutions. Dependencies on specific tools (PostHog, Lovable, Cursor) may limit the reproducibility of results in different technical environments.

The early-stage startup environment created competing priorities that may have affected intervention implementation and evaluation. The small team size limited internal validation opportunities and stakeholder feedback diversity. Results may not apply to organizations with different resource levels, decision-making processes, or growth stages.

The research period may have been influenced by seasonal business patterns, particularly in the Italian market. Summer approaching during the second cycle may have affected B2B decision-making patterns. The timing of the exhibition coinciding with measurement periods may have created artificial traffic spikes.

The absence of comprehensive pre-intervention data limited the ability to establish clear performance baselines. Historical website performance metrics were not available for comparison, making it difficult to assess the true magnitude of improvements achieved through the interventions.

6 Conclusions

This thesis investigated how UI/UX design improvements, systematic analytics implementation, and integrated social media marketing enhance website performance for an early-stage AI startup through a Canonical Action Research (CAR) framework. The study employed two iterative cycles combining quantitative analytics with qualitative user research to address conversion optimization challenges in a resource-constrained startup environment. The research framework integrated established theoretical foundations from Human-Computer Interaction, web analytics theory, and digital marketing literature with Continuous Experimentation (CE) principles to enable systematic, hypothesis-driven optimization within academic research constraints. Multiple concurrent interventions and external factors (promotional activity, referral mix, brand familiarity, and seasonality) were present across both cycles. Findings therefore indicate associations rather than isolated causal effects of any single change.

6.1 Theoretical Framework Integration and Validation

The study integrated multiple theoretical domains to address startup website optimization challenges. User Experience (UX) and User Interface (UI) design principles, grounded in conversion rate optimization theory, guided website interventions that coincided with strong engagement metrics (17% bounce rate, 5 minutes 15 seconds session duration). However, these principles were insufficient on their own to address deeper communication barriers in a complex technical domain and cannot be isolated as the sole contributors to observed outcomes.

Web analytics theory, implemented through a comprehensive PostHog tracking setup, enabled systematic measurement of behavior patterns and funnel performance. This framework supported data-informed decisions, such as renaming sections or adding new elements in strategic places, by revealing traffic composition and conversion frictions that qualitative assessment alone would likely miss. Instrumentation does not, by itself, establish causality, so all inferences are treated as correlational.

Digital marketing theory, particularly B2B social engagement, showed measurable but indirect associations with website performance. LinkedIn was the second-largest traffic source (256 sessions, 20.5%), functioning primarily as a brand-awareness amplifier rather than a direct conversion channel. This aligns with multi-touchpoint journey models in professional services. Effects on conversion should be interpreted as suggestive, not causal, given concurrent activities.

The integration of CE principles within the CAR methodology enabled hypothesis-driven testing and iterative optimization under academic constraints. CAR provided the overarching structure for organizational learning, while CE guided experimental design and measurement. The integration demonstrates feasibility but does not isolate effect sizes of individual interventions, which would require controlled rollouts.

6.2 Research Questions: Findings and Implications

6.2.1 RQ1: CAR and CE Integration for Website Optimization

The CAR+CE integration enabled effective, resource-aware optimization with important caveats. Two full cycles produced organizational improvements and academic insights; three of seven hypotheses were supported, two partially supported, and two inconclusive. Engagement gains did not translate proportionally to conversion, indicating that methodological rigor must be paired with work on user comprehension barriers. All findings are correlational given confounding factors present during measurement.

However, the research reveals a critical limitation: surface-level engagement improvements do not automatically translate to conversion optimization. Despite achieving satisfactory user engagement metrics, conversion rates remained modest, indicating that methodological rigor must be coupled with deeper understanding of user comprehension barriers in complex technical domains.

6.2.2 RQ2: Design Elements and Content Strategies Impact

Design and content analyses suggest a provisional hierarchy of conversion influence for this context: semantic clarity > information architecture > tangible demonstrations > visual design. Qualitative data from cycle two surfaced four key barriers (offer ambiguity, jargon interpretation, weak information hierarchy, and demand for tangible demonstrations). These results prioritize message clarity and IA before visual refinements, subject to confirmation via controlled tests.

6.2.3 RQ3: Social Media Integration and Lead Generation

Social media acted largely through indirect awareness rather than direct lead capture. LinkedIn contributed 256 sessions (20.5%), while Google contributed 339 sessions (27.1%), consistent with social exposure followed by brand search. An offline exhibition produced a clear 51-session spike on June 5, 2025, suggesting that integrated omnichannel execution is more effective than isolated tactics.

6.3 Methodological Contributions

The study shows how CAR's stakeholder engagement and learning complement CE's hypothesis validation and iteration. Tensions emerged between academic evaluation cycles and startup speed, with review and compliance steps delaying hypothesis iteration. The approach is practicable, but isolating effects requires designs such as staggered releases or holdouts.

6.4 Practical Implications for Early-Stage AI Startups

For early-stage AI startups, this research suggests to allocate resources first to semantic clarity and information architecture, then to demonstrations (videos or interactive

prototypes), and only then to visual polish. Furthermore, treat social platforms as awareness and qualification channels that support, not replace, search-led discovery.

6.5 Future Work

6.5.1 Continued Organizational Development

Future experiments should include randomized or staggered rollouts (feature flags), A/B tests of value-proposition wording, interrupted time-series around campaign starts, and segmented analyses by traffic source to reduce confounding. Track longitudinal conversion with stable instrumentation and pre-registered success metrics. Evaluate demonstration content via experiment rather than pre/post only.

6.5.2 Theoretical and Methodological Research Directions

Several theoretical questions emerge from this research that warrant investigation independent of the target organization. The conversion hierarchy model identified in this study requires validation across different AI service contexts and startup stages to establish generalizability. Future research should investigate whether the semantic clarity > information architecture > visual design hierarchy applies consistently across complex technical service domains.

The integration of qualitative user research with quantitative analytics in startup contexts presents opportunities for methodological advancement. Research is needed to develop frameworks for optimal timing of qualitative data collection within rapid iteration cycles, and to establish guidelines for sample size requirements in startup user research where resources are constrained but insights are critical.

The relationship between CAR methodology and CE principles warrants deeper theoretical investigation. While this study demonstrated successful integration, clearer frameworks are needed for distinguishing research-level interventions from product-level optimization, particularly in contexts where organizational learning and product development objectives overlap significantly.

The effectiveness of omnichannel marketing strategies in B2B startup contexts requires systematic investigation across different industry sectors and geographic markets. Research is needed to understand optimal integration points between offline engagement and digital conversion optimization, particularly for complex technical services where trust-building and capability demonstration are critical conversion factors.

Finally, the study's findings regarding terminology and jargon barriers in AI service communication suggest a need for broader investigation into technical communication effectiveness in startup marketing contexts. Research should explore optimal approaches for translating technical capabilities into accessible value propositions without oversimplification or accuracy loss.

6.6 Final Remarks

This research demonstrates that systematic, theory-driven website optimization is achievable in resource-constrained startup environments through appropriate methodological integration. All conclusions are stated as associations given concurrent changes, but the successful application of CAR principles combined with CE frameworks provides a model for bridging academic rigor with practical business requirements. However, the findings emphasize that conversion optimization in complex technical domains should prioritize comprehension over aesthetics.

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A Interviews Consent Form

INFORMED CONSENT FORM

Title of Research Project

Improving Website Conversion Through UX Design and Analytics: A Case Study in an AI Startup

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Purpose of the Study

You are invited to participate in a research study that aims to understand how people interpret and experience the website of an AI consulting startup. The goal is to evaluate whether the website communicates a clear message and offers a user-friendly experience. Your feedback will help inform improvements in website design, usability, and communication.

What Participation Involves

- You will be asked to visit a live website and describe your impressions, understanding, and usability experience.
 - You may be asked open-ended questions such as "What do you think this company does?" and "What was clear or unclear to you?"
 - The session will last approximately 15–30 minutes.
 - With your permission, notes may be taken.
 - You may also be asked to complete a short follow-up questionnaire.
-

Voluntary Participation

Participation is entirely voluntary. You may refuse to participate or withdraw at any time without giving a reason. There are no consequences for choosing not to participate.

Figure A1: Interviews Consent Form (Page 1).

Confidentiality and Data Handling

- Your identity will remain anonymous in any report, presentation, or publication.
 - No sensitive personal data will be collected.
 - Any notes or questionnaire responses will be stored securely and used solely for academic research.
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Consent

Please check the appropriate boxes:

- I have read and understood the information provided above.
 - I understand that my participation is voluntary and that I can withdraw at any time.
 - I give permission for the researcher to take notes during the session.
 - I consent to the use of anonymized quotes or comments in research reports or publications.
-

Contact Information for Questions about Your Rights as a Research Participant

If you have questions about your rights as a research participant, or wish to obtain information, ask questions, or discuss any concerns about this study with someone other than the researcher(s), please contact the Secretary of the Ethics Committee Information & Computer Science: ethicscommittee-CIS@utwente.nl

Participant Name: _____

Signature: _____

Date: _____

Researcher Signature (if in person): _____

Figure A2: Interviews Consent Form (Page 2).

B Interview questions

In order:

1. What do you think this company does?
2. What makes you think that?
3. What was clear or unclear?

C AI Usage Statement

During the preparation of this work, the tool ChatGPT (OpenAI) was used to check grammar and improve the quality of English sentences. The generated suggestions were reviewed, edited, and adapted by the author, and full responsibility for the final content and its accuracy has been taken.