An AI-Based Approach to Measuring Return on Investment in UX Design

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Abstract

Measuring the Return on Investment (ROI) in User Experience (UX) Design is essential for demonstrating the business value of design decisions. However, this process remains challenging due to the intangibility of outcomes, the difficulty of isolating causal factors, and the lack of standardized measurement practices. With the advancement of Generative Artificial Intelligence (GenAI) and intelligent agents, new opportunities emerge to automate UX data analysis and connect user experience metrics with business performance indicators. This doctoral research investigates how Artificial Intelligence (A) can support the measurement of ROI in UX Design, adopting the Double Diamond model to structure an iterative research process across four phases: Discover, Define, Develop, and Deliver. Building on literature reviews, empirical studies, and practical applications, the study proposes an AI-supported framework that integrates leading and lagging indicators to measure both user experience and business outcomes. The expected contributions include: (i) a framework to assist organizations in ROI measurement through AI-driven analysis; (ii) a case study demonstrating its application; and (iii) an updated theoretical overview that connects UX, AI, and business strategy.

Keywords

ROI in UX Design, User Experience Measurement, Artificial Intelligence, Human–AI Collaboration

1. Research Problem

Measuring the Return on Investment (ROI) in the User eXperience (UX) Design process is a fundamental task for business success [1]. Through such measurement, it becomes possible to make more accurate strategic decisions and to understand the real impact of UX Design on organizational outcomes [2]. ROI is understood as the ratio between the financial return (or cost savings) and the investment made, allowing the identification of whether the return was greater or smaller than the investment [3]. UX Design, in turn, is conceived as a structured and iterative process of building or improving solutions based on direct interaction with users [4].

Measuring ROI in UX Design offers relevant benefits, such as guiding evidence-based decision-making, demonstrating the financial value of design solutions, and promoting the continuous optimization of products and processes [5]. However, despite its importance, significant challenges remain to be overcome [2]. In some cases, the initial investment is high, and the return occurs only after a long period, which makes it difficult to objectively demonstrate ROI in UX Design [1]. There are also situations in which returns are intangible or difficult to measure, such as brand reputation, which is influenced by multiple factors that are not directly quantifiable [6, 7].

Moreover, isolating results derived from the UX Design process from those resulting from other organizational initiatives is complex [8], which makes it difficult to demonstrate ROI with precision. Another challenge involves the use of metrics correlated with ROI—such as customer satisfaction or retention—that, although related, are not sufficient to prove ROI itself [2]. With the advancement of Generative Artificial Intelligence (GenAI)—capable of creating, synthesizing, and analyzing content from large volumes of data [9] — new possibilities emerge to support product development and the

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measurement of its outcomes [10]. In parallel, the use of Intelligent Agents—autonomous AI-driven systems that collaborate with each other to perform specific tasks [11]—contributes to automating and deepening UX data analysis, enabling a more precise understanding of the challenges involved in ROI measurement in Design [12].

In this context, the research problem guiding this study emerges: **How can ROI be measured in the UX Design process through the use of Artificial Intelligence (AI)?** To address this question and guide the doctoral research, the study adopts a methodology based on the *Double Diamond* model [13], which is structured into four main phases — Discover, Define, Develop, and Deliver - combining divergent and convergent thinking to support creative and investigative processes. This approach was chosen due to its applicability in research focused on solving complex problems, such as measuring the impact of UX Design on business outcomes, allowing the problem to be explored in depth and solutions to be proposed based on empirical evidence [14].

As contributions, this doctoral research aims to: (i) propose a ***framework*** that supports companies in measuring ROI in UX Design through the use of AI; and (ii) develop a **case study** that describes the application of the *framework* and its results. This paper is structured as follows: Section 2 outlines the knowledge gap, highlighting the research gaps identified in the literature; Section 3 describes the research methodology; Section 4 presents the doctoral research timeline, showing what has been completed and what is planned; Section 5 presents preliminary results; and finally, Section 6 presents the expected contributions of this research.

2. Knowledge Gap

Recent literature demonstrates significant advances in the incorporation of AI into the UX Design process, highlighting the potential of these technologies to automate design stages, enhance interfaces, and generate more personalized experiences [12]. However, an analysis of the existing body of knowledge reveals that the relationship between AI and the measurement of business outcomes—particularly Return on Investment (ROI)—remains fragmented and insufficiently explored in a systematic manner [10].

The reviewed studies focus predominantly on two main axes: (i) the application of AI as a design support tool, aimed at optimizing interfaces and individual user experiences [12, 15], and (ii) the understanding of the collaborative role between humans and intelligent systems in design processes [10, 16]. Although these approaches have contributed to broadening the understanding of automation and co-creation within the UX context, they have not made much progress in measuring the organizational or financial impact resulting from these practices [17].

Furthermore, most investigations concentrate on usability, satisfaction, or engagement metrics while neglecting indicators that connect UX outcomes to strategic business objectives [17]. The absence of consolidated frameworks that integrate UX metrics, business data, and AI-driven predictive analyzes highlights a central methodological gap: as an emerging field, there is still no consensus on how AI can effectively support ROI measurement in UX Design processes in a structured, reliable, and scalable way [15].

Another limitation identified is the scarcity of empirical studies validating, in real organizational contexts, the effectiveness of hybrid human–AI collaboration models applied to performance measurement [16]. While there is a consensus on the potential of AI to optimize decision-making and identify complex behavioral patterns, research on how these insights can be translated into business value metrics remains in its early stages [12].

Therefore, this doctoral research seeks to address these gaps by proposing an **AI-supported *framework* for measuring ROI in UX Design**, combining qualitative and quantitative methods to (i) capture performance and experience data in an automated way, (ii) translate UX insights into organizational impact metrics, and (iii) promote collaboration between humans and intelligent agents throughout the analysis and decision-making process.

3. Research Method

This section presents the research methodology adopted and the current status of what has been accomplished so far in this doctoral study. The *Double Diamond* model was adapted as the methodological *framework* to organize the research stages in a logical and iterative manner [13]. This approach facilitates the integration between theoretical exploration, empirical investigation, and the practical construction of an artifact — a *framework* for measuring the impact of UX Design. Figure 1 provides an overview of the general methodology, indicating the phases already completed and those currently in progress. Following paragraphs describe the activities carried out in each phase.

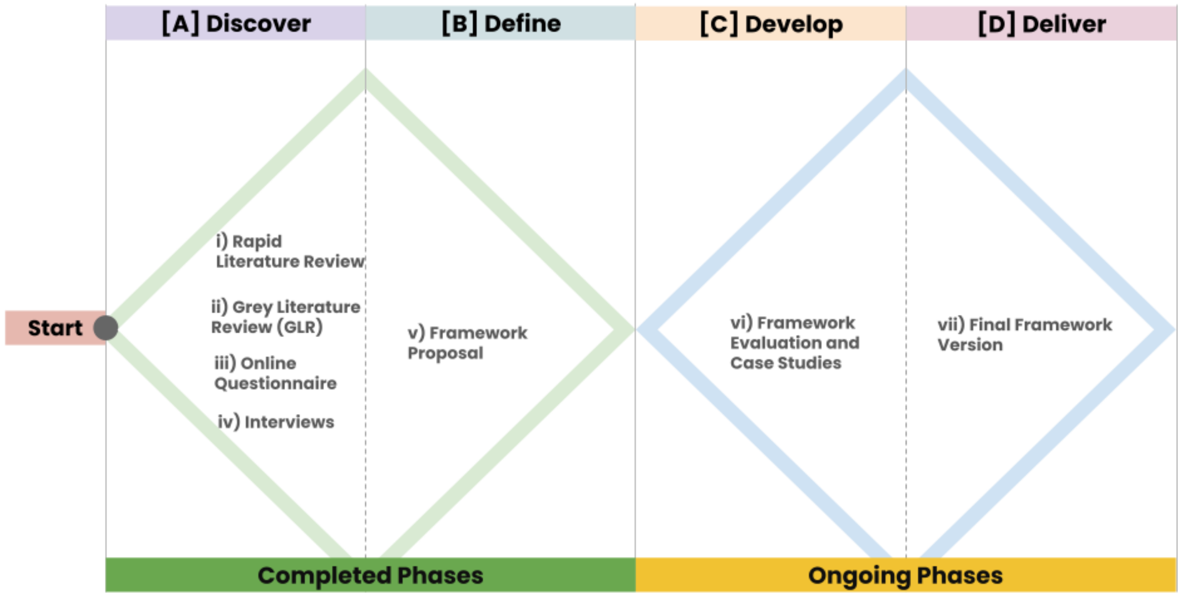

Figure 1: Overview of the doctoral research methodology based on the adapted *Double Diamond* model.

Discovery phase included a Rapid Literature Review (RLR) [18], chosen for its efficiency in mapping the state of the art while ensuring methodological rigor. In parallel, a Systematic Grey Literature Review (GLR) [19] was conducted to capture industrial and non-academic perspectives often absent from traditional literature, thus complementing the academic findings. Furthermore, two initial field studies were performed — an exploratory online questionnaire and semi-structured interviews with UX and digital product professionals [20]. The questionnaire was selected to obtain a broad and quantitative overview of practitioners' perceptions, whereas the interviews provided qualitative depth, allowing for a richer understanding of the practices, challenges, and contextual factors influencing how organizations measure UX outcomes.

i) Rapid Literature Review (RLR) began with the definition of the search string [21] and the selection of four scientific databases relevant to the fields of Human–Computer Interaction (HCI) and Software Engineering: IEEE Xplore, ACM Digital Library, Scopus, and SOL. A total of 1,305 articles were initially retrieved. After applying inclusion and exclusion criteria—considering a ten-year time window and thematic relevance—and a Quality Assessment (QA), 17 articles were considered relevant. Data extraction was conducted through open coding [22], followed by thematic analysis [23] to group practices and evidence by analytical dimension. The entire process involved peer review and cross-validation among researchers, ensuring methodological rigor, consistency, and fidelity to the original data.

Open coding consisted of an exploratory reading of raw data (interviews, open-ended questionnaire responses, and literature) to identify meaning units without predefined categories. Each significant excerpt was labeled with a code representing its central idea [22]. For example, when a excerpt described using ChatGPT to generate personas or structure questionnaires, the excerpt was coded as *tool*. This phase prioritized analytical sensitivity and the emergence of multiple themes from participants' discourse. Subsequently, thematic analysis organized the codes into interpretive categories and recurring patterns, enabling the construction of broader conceptual dimensions [23]. This analysis grouped findings into themes such as barriers, best practices, gaps, and measurement criteria, providing direct input for refining the *framework*. The same methods were applied to analyze data from the other studies. All data can be found in this spreadsheet.

ii) Grey Literature Review (GLR) followed the guidelines proposed by Garousi, Felderer, and Mäntylä [19], justified by six affirmative answers to the seven questions that assess the need for this type of study. Term collection was conducted through a survey with 34 UX Design and Product professionals, whose responses guided the formulation of the search string and the selection of key sources (Medium, Nielsen Norman Group, and UX Design Collective). A total of 3,038 articles were identified and filtered using inclusion and exclusion criteria, with support from the Generative AI tool (ChatGPT-4) to automate and validate the screening process through prompts tested under controlled error margins. After applying a quality checklist, 904 articles remained. Data extraction and analysis followed the same method as the previous review, resulting in 2,305 excerpts organized by segments, contexts, and outcomes, ensuring rigor and consistency in synthesizing practical and conceptual evidence from grey literature.

iii) Online questionnaire was composed of twelve questions, including demographic information and items related to the measurement of UX Design outcomes, aligned with the three research questions (measurement, challenges, and objectives). The instrument was developed through rounds of review among researchers, followed by a pilot test with two UX professionals, which confirmed the clarity and adequacy of the questions. The questionnaire was distributed via Google Forms between February and March 2024, using convenience sampling and dissemination through social networks and professional channels. A total of 34 valid responses were obtained and analyzed qualitatively using the open coding and thematic analysis methods. The results were organized in spreadsheets containing codes and descriptions.

iv) Semi-structured interviews were also conducted with ten UX Design professionals, including designers, product managers, and researchers. The interview guide was based on the research questions and divided into sections covering professional profile, measurement practices, and AI usage. Prior to implementation, a pilot test with two participants ensured the clarity and timing of the sessions. Participants were recruited via social media, and the interviews—conducted through Google Meet between March and April 2025 — totaled 3 hours and 36 minutes of recordings. All interviews were conducted with formal consent (Informed Consent Form) and followed a standardized protocol. Transcripts were analyzed qualitatively using the same methods as in previous stages.

In the **Definition** phase, the collected data were synthesized to support the initial proposal of a UX impact measurement *framework* aligned with business metrics. This theoretical construction was guided by evidence derived from the literature and empirical studies. The methodology used for building the first model was based on Shehabuddeen et al. [24], who define a *framework* as a conceptual, static, dynamic, and applied structure that organizes and guides the understanding and use of a complex phenomenon.

In this stage, starting in September 2025, the researcher will undertake a six-month research stay at Tampere University in Finland, developing part of this doctoral project at the GPT-Lab[1], under the co-supervision of Professor Pekka Abrahamsson, an internationally recognized authority in software engineering, agile methodologies, and AI applications in business. Collaboration with the GPT-Lab will enable deeper investigation in a highly innovative environment, combining theoretical rigor with experimental practice, particularly in evaluating the proposed *framework* through the use of AI Agents, thereby strengthening both the scientific foundation and international reach of this research.

The **Development** phase is currently in progress and involves two rounds of evaluation with domain experts. The first aims to test the clarity, applicability, and potential usability of the *framework*. Based on

[1]The *Generative Pre-trained Transformer Laboratory* (GPT-Lab) at Tampere University focuses on artificial intelligence research, particularly large language models and human-computer interaction. More information at: https://webpages.tuni.fi/gplab/.

feedback, an initial refinement will be performed, followed by a second evaluation round that will result in the revised version of the model. Finally, the **Delivery** phase will culminate in the consolidation of the final version of the *framework* and the production of complementary artifacts (such as guides and conceptual maps), along with the systematization of the results in scientific papers and academic communications.

4. Timeline

This section presents the planned activities until the end of this research and timeline (see Fig .2). Marked with an "X" in space represents that an activity will be carried out in a month and year. Phase A and B have already been completed, while phase C is underway.

Phases	Activities	2023		2024				2025				2026				2027	
		3º Tri	4º Tri	1º Tri	2º Tri	3º Tri	4º Tri	1º Tri	2º Tri	3º Tri	4º Tri	1º Tri	2º Tri	3º Tri	4º Tri	1º Tri	2º Tri
[A] Discover	Execution of the Rapid Literature Review (RLR)	x	x														
	Execution of the Grey Literature Review (GLR)		x	x	x												
	Execution of the Online Questionnaire				x	x											
	Execution of the Interviews						x	x									
[B] Define	Development of the First Version of the Framework							x									
	Writing and Examination of the PhD Qualification							x	x								
[C] Develop	Start of the doctoral sandwich program at the foreign institution at GPTLab									x	x	x	x				
	Case Study with Companies for Framework Evaluation									x	x	x	x				
[D] Deliver	Final Version of the Framework													x	x		
	Dissemination of Results (e.g., publication of papers in conferences and journals)						x	x			x	x			x	x	
	Thesis Writing and Defense															x	x

Figure 2: Planned activities until the end of this research and timeline.

5. Preliminary Results

This section succinctly presents the main results obtained from the four studies conducted, as well as the first proposed version of the *framework*. In this context, practices are understood as the different forms of action and routines associated with the process of measuring business results within UX Design [25]. The practices identified across the studies include measurement approaches based on performance metrics classified as Leading and Lagging indicators [26]. Lagging indicators refer to direct economic impact — that is, metrics that demonstrate realized financial returns [27]. Conversely, leading indicators represent indirect economic impact, composed of predictive and intermediate metrics such as engagement, satisfaction, retention, and adoption, which act as a bridge between user experience and business performance [26]. Figure 3 illustrates the role of these metrics throughout the UX Design process, highlighting their function in connecting design practices with measurable business outcomes.

Experience metrics, defined as intermediate metrics that signal how UX Design activities affect the user experience [25], were identified and consolidated throughout the studies conducted. Table 1 presents each metric, its corresponding description, and the studies in which it was observed (listed from i to iv, as illustrated in Figure 1).

Interview analysis revealed both the main **objectives** and **challenges** associated with measuring ROI in UX Design. The percentages presented for each category represent the proportion of mentions and codes identified in the total set of thematic extractions, reflecting how frequently each theme was discussed by participants. Regarding the objectives of measurement, three main categories were identified. The first and most frequent objective is **validation and prioritization of initiatives (46.2%)**, which emphasizes the importance of measuring results to assess whether UX activities truly generate business value. ROI-oriented data support the validation of design decisions, help prioritize initiatives with measurable impact. The second objective, **communication with stakeholders (33.3%)**,

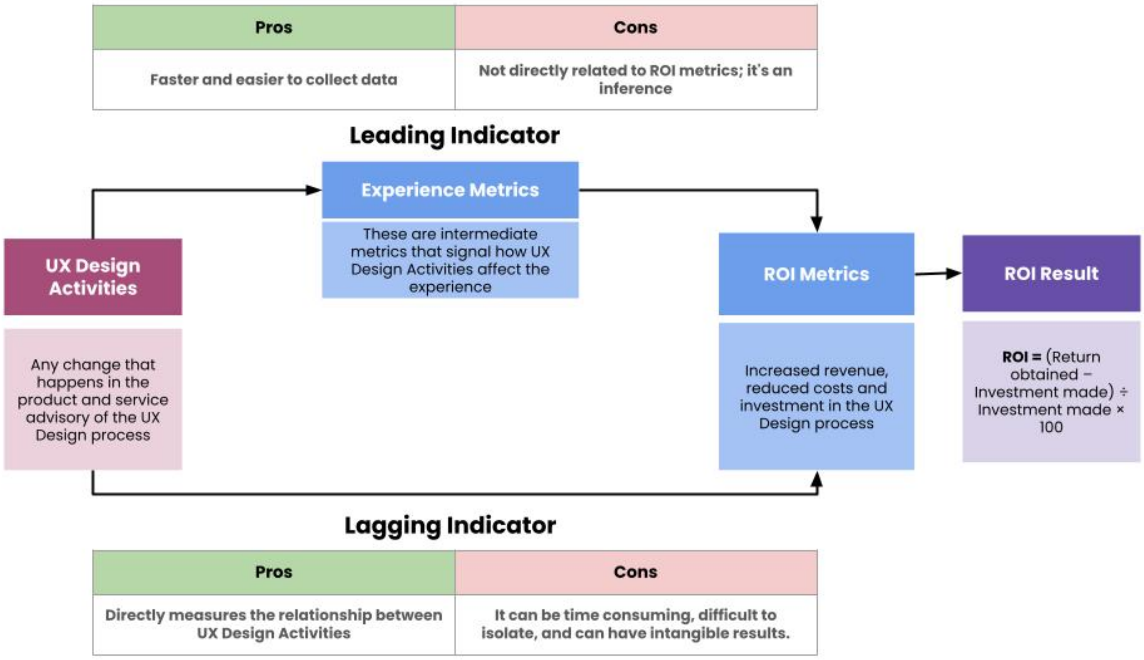

Figure 3: The role of metrics throughout the UX Design process.

Table 1
Experience metrics identified across studies and their relationship with ROI - (i) Rapid Literature Review; (ii)...

Metric	Description	i	ii	iii	iv	Relation to ROI
Task success rate	Percentage of users who successfully complete a task.	X				Indicates efficiency and clarity of the interface, affecting conversion.
Task time	Average time required to complete a task.	X	X			Reduces support costs and increases user productivity.
Error rate	Percentage of errors during task execution.	X	X			Fewer errors lead to cost reduction and higher satisfaction.
User engagement	Frequency of user interaction with features or sessions.		X		X	Higher engagement increases LTV and conversion rate.
Retention rate	Percentage of users who continue using the product over time.	X	X		X	Indicates satisfaction and potential for recurring revenue.
User satisfaction	Overall satisfaction level with the product or service.	X		X	X	Satisfied users are more likely to repurchase and recommend.
Conversion rate	Percentage of users completing a business goal (e.g., purchase, registration).	X	X		X	Directly links UX improvements to revenue growth.
Cart abandonment rate	Percentage of users abandoning a purchase before completion.		X			Lower abandonment increases sales conversion.
Time to first click	Time until the first user interaction.	X				Reflects clarity and ease of initial navigation, reducing frustration.
Operational efficiency	Reduction in time or effort for development and support processes.		X		X	Reduces operational costs and enhances ROI.
Learning time for new features	Time required for users to master new functionalities.		X			Shorter learning time reduces support needs and accelerates adoption.
Loyalty and recommendation (NPS)	Users' likelihood to recommend the product or service.	X	X	X	X	Direct correlation with loyalty, retention, and brand value.

highlights measurement as a mechanism for providing quantitative and qualitative evidence that fosters clearer communication with executives and other departments, building trust and facilitating data-driven decision-making. Finally, the third objective, **professional growth and recognition (17.9%)**, demonstrates that measuring UX outcomes strengthens both the visibility and legitimacy of UX work within organizations.

Conversely, the analysis also revealed a set of **challenges in measuring ROI in UX Design**. Analyzing the challenges helps us understand how the framework should act to mitigate them. The first and most frequent challenge identified was **technical difficulties and dependencies on other teams (38.5%)**, related to technological limitations, data inconsistencies, and the need for collaboration with areas such as product, marketing, or engineering — factors that often delay or hinder integrated analyzes. The second challenge concerns the **lack of structure and measurement processes (23.0%)**, marked by the absence of systematic methods, tracking systems, and formalized analytical structures within organizations, making data collection, comparison, and reliability difficult. The third challenge identified was **isolation of variables and causality (17.9%)**, representing the difficulty of attributing business outcomes to specific UX changes due to multiple external factors. Finally, the **complexity of communicating results (10.3%)** emerged, associated with the difficulty of translating UX data into understandable and actionable insights for managers and decision-makers.

Interview analysis also mapped how professionals are currently using **Artificial Intelligence (AI)** in their daily UX Design activities. The most recurrent use concerns **task acceleration and optimization (36%)**, where participants reported employing AI to automate routines, speed up analyzes, structure texts, and summarize information. Next, the theme of **technical and ethical risks (24%)** was highlighted, reflecting concerns about calculation errors, data leakage, and the uncritical or unsupervised use of AI. Lastly, the category **AI as a creative and communication tool (16%)** emerged, associated with the use of language models and content generation in ideation tasks, script development, persona creation, and text standardization—promoting clarity and consistency in communication across teams.

Framework (see Fig. 4) is organized around three complementary dimensions: **measurement objectives**, **measurement practices**, and **structural challenges**. The objectives reflect the three main motivations identified in the interviews, which together reinforce the strategic role of measurement as a decision-making and value-demonstration tool. The measurement practices are structured around **leading and lagging indicators**, enabling the capture of both immediate UX outcomes and their long-term business impacts. Each phase happens one after the other, hence the use of the arrows. AI functions as an **integration and analytical intelligence mechanism**, automating data collection and analysis, and identifying correlations between user experience metrics and financial outcomes. Finally, the *framework* acknowledges and incorporates the three main measurement challenges, proposing an adaptable model that combines theoretical foundations, empirical evidence, and technological support.

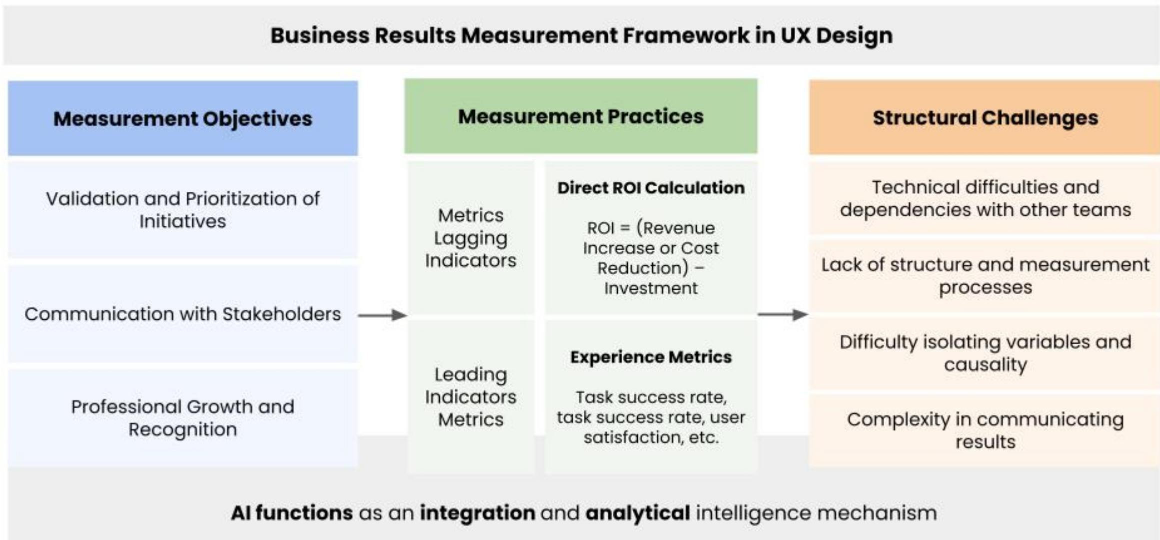

Figure 4: AI-supported *framework* for ROI measurement in UX Design.

Next stage of the research involves **applying the *framework* in an AI-supported context**, assisting UX Design teams in ROI measurement while simultaneously evaluating its effectiveness and acceptance. To conduct this evaluation, the **Technology Acceptance Model (TAM)** [28] will be employed, a theoretical model widely used to understand the factors influencing the adoption and use of new technologies and information systems. TAM posits that **perceived usefulness** and **perceived ease of use** are key determinants of **user acceptance** and **intention to use** a technology. The empirical validation will follow a **mixed-method approach**, involving the **prospection of partner companies** and collaboration with the **GPT-Lab**, which will provide technical and methodological support for the experimental implementation.

6. Expected Contributions

As the main contributions of this doctoral research, it is expected to deliver: (i) an applied *framework* to support companies in the measurement of ROI in UX Design through the use of Artificial Intelligence (AI), promoting the integration of user experience metrics with business performance indicators and enabling a data-driven understanding of design impact; and (ii) an empirical case study that documents the practical application of the *framework*, presenting its implementation process, results, and lessons learned in real organizational contexts, thereby demonstrating its feasibility and value for both academic and industrial environments.

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Generative AI Statement

The authors confirm that no generative AI tools were used in the writing, analysis, or preparation of this manuscript.

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