Designing Hydration as Data

Design and engineering of an integrated system for real-time fluid intake measurement in high-performance cycling

School of Design
Master of Science in Design & Engineering

Supervisor:
Andrea Bonarini

Candidate:
Emanuele Tonarini - 249916

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ABSTRACT

With this thesis, I set out to explore a domain that lies at the intersection of my personal background, athletic practice, product design and engineering: the relationship between data, performance, and the lived experience of road and gravel cycling.

In professional road cycling, performance emerges from the optimization of a large number of factors, each contributing marginally yet decisively to the final competitive outcome. In WorldTour differences between athletes are often measured in a few watts, the availability of accurate and continuous data has become a necessary condition to support strategic decisions in training, racing, and nutrition. This paradigm, commonly referred to as marginal gains, highlights how the ability to measure and control even seemingly secondary inputs can meaningfully influence performance.

Among the variables that significantly affect endurance performance, hydration and in-activity nutrition play a central role. Unlike parameters such as power output, heart rate, or cadence, however, actual fluid and nutrient intake during exercise is still largely managed through indirect estimates or standardized protocols.

In this work, hydration is not understood as the simple intake of water, but as the ingestion of functional fluids containing carbohydrates and electrolytes, such as isotonic drinks, saline solutions, and maltodextrin-based mixtures.

Despite this awareness, a substantial gap remains in the ability to directly, continuously, and objectively measure fluid intake during cycling activity. The absence of such data limits the possibility of rigorously correlating nutritional strategies with performance trends and developing truly personalized approaches. This gap defines the core objective of the present thesis: the design and development of a system capable of measuring fluid intake during cycling under real-world conditions.

My project adopts an integrated design and engineering approach, combining state-of-the-art analysis, design brief definition, conceptual development, and the realization of functional prototypes. The measurement system is integrated into an existing bicycle component—the bottle cage—transforming it into a smart device capable of collecting data without significantly interfering with the athlete's experience. Two smart bottle cage prototypes are developed and tested, each representing a different design interpretation of the same functional objective.

The results demonstrate the potential of such a system to support more informed, performance-oriented nutritional strategies and establish a foundation for future research and industrial development in high-performance sports product design.

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1.0 Introduction

1.1 Background and inspiration

This thesis grows out of my passion in cycling, bike mechanics and everything releated to the bike industry. The motivation for this thesis is deeply personal. My journey into the world of cycling began when I was thirteen years old, watching the 15th stage of the 2014 Giro d'Italia. That day, I saw the race pass through near my hometown, in Saronno, before climbing toward Plan di Montecampione, where Fabio Aru claimed a decisive victory, while Rigoberto Urán successfully defended the pink jersey. What might have been just a sporting event became a defining moment in my life. Seeing the riders pass in front of me transformed cycling from a distant spectacle into something tangible, human, and profoundly inspiring.

From that moment on, cycling became a central thread in my life, guiding me over the following twelve years through continuous study, personal practice, and an ever-growing curiosity. I followed races around the world, trained as an athlete, and gradually developed a desire to understand not only how performance is achieved, but how it can be designed, measured, and improved.

Since this January, this personal trajectory has also become professional. I started working as an R&D engineer at Vision-FSA, a company that develops components used by eight professional teams, including three WorldTour teams. Entering the bike industry from within has represented a significant milestone in my path: for the first time, the passion that shaped my formative years and the skills developed through my academic journey have converged into a real, concrete professional context. This thesis stands precisely at this intersection, representing both the synthesis of a long-standing personal passion and the beginning of my active involvement in the cycling industry.

In recent years, cycling—and endurance sports more broadly—has undergone a significant shift toward the systematic use of data. This shift is not limited to increased availability, but reflects a growing need for more precise and continuous measurement of the variables that influence performance. In professional road cycling, particularly at the WorldTour level, the margin separating an athlete competing for victory from one finishing outside the points is often extremely narrow. In this context, small differences in energy efficiency, effort management, or nutritional intake can translate into variations of only a few watts, yet be sufficient to determine substantially different competitive outcomes.

This condition has contributed to the widespread adoption of the concept of marginal gains, according to which overall performance improvement does not result from a single dominant factor, but from the accumulation of many small, systematic optimizations. Aerodynamics, riding position, training methodology, equipment choices, and race strategy are all analyzed, measured, and refined with the goal of reducing energy losses and improving efficiency. Within this framework, data are no longer merely descriptive, but become decision-making tools, directly influencing training planning, tactical choices, and nutritional strategies during competition.

At the same time, advances in measurement technologies have enabled the continuous monitoring of an increasing number of performance-related variables. Power output, heart rate, cadence, elevation profile, and training load are now routinely collected in professional cycling, supporting a highly data-driven approach to performance management. However, not all variables that significantly affect performance are currently measured with the same level of accuracy and continuity.
In particular, hydration and nutritional intake during cycling activity remain areas in which real data are often estimated, approximated, or reconstructed after the fact. Despite extensive scientific literature highlighting the crucial role of fluid and nutrient intake in sustaining prolonged effort, the lack of direct, continuous, and objective measurements limits the ability to establish robust correlations between intake strategies and performance outcomes. This limitation is especially relevant in high-level competition, where suboptimal nutritional management can lead to performance decay sufficient to compromise results, even when physical preparation is otherwise optimal.

In my work, hydration is not considered as the mere intake of water, but as a more complex process involving the ingestion of functional fluids containing carbohydrates and electrolytes, such as isotonic drinks, saline solutions, and carbohydrate-based mixtures. Liquid carbohydrate intake plays a central role in endurance nutrition due to its absorption characteristics and the possibility of precisely modulating energy supply during exercise. Recent literature identifies the rate of carbohydrate absorption as one of the main physiological bottlenecks to performance, making nutritional strategy a determining factor alongside training and effort management.

A liquid intake also represents a measurable and controllable interface between the athlete and the physiological system, opening new opportunities for monitoring and optimization.
Despite this awareness, hydration and nutrition in professional cycling are still commonly managed through standardized protocols based on generic timing rules, theoretical estimates, or indirect measurements such as body mass variation before and after exercise. These approaches rarely account for individual differences between athletes, changing environmental conditions, or the specific dynamics of effort. Moreover, the absence of continuous, objective data makes it difficult to rigorously analyze the effects of different fluid compositions—such as varying carbohydrate or electrolyte concentrations—under comparable external conditions.

This gap constitutes the core motivation behind the present thesis project. The objective is not simply to verify whether an athlete hydrates during activity, but to understand how much, when, and what is actually consumed during effort, and how this information can be related to performance evolution. The ability to reliably record real intake of functional fluids enables the development of personalized nutritional strategies, the comparison of different nutritional solutions under controlled conditions, and a more accurate evaluation of their impact on performance.

The project addresses this challenge through an integrated design and engineering approach, structured around an initial state-of-the-art analysis, followed by the definition of a design brief, conceptual development, and functional prototyping. In particular, the work focuses on integrating a measurement system into a component already present on the bicycle—the bottle cage—transforming it into an intelligent device capable of collecting data under real riding conditions without significantly altering the athlete's experience.

Throughout my thesis, two smart bottle cage prototypes are developed and tested, representing different design interpretations of the same functional objective. Through an iterative process combining conceptual design, technical development, and prototyping, the work explores both the potential and the limitations of solutions aimed at measuring hydration as a critical physiological input to performance. The results provide a foundation for future research and industrial applications, contributing to the broader discussion on the role of data in the design of performance-oriented sports products.

1.2 Brief research question

Grounded in the growing relevance of data-driven performance optimization in elite cycling, and in the current lack of direct measurements of in-activity hydration, this thesis is structured around a central research question that bridges physiology, measurement, and product design. While power, heart rate, and cadence are continuously monitored, fluid and carbohydrate intake during real riding conditions remains largely inferred rather than measured. This gap motivates a design-led investigation into how hydration can be transformed from an estimated parameter into a measurable variable.

CORE QUESTION

How can fluid intake during cycling activity be directly measured in real-world conditions through an integrated product-system, without significantly interfering with the athlete's performance and experience?

SUB RESEARCH QUESTION

1. What are the technical and physiological constraints associated with measuring hydration during cycling?
2. Which sensing principles are most suitable for indirect measurement of fluid intake in a dynamic environment?
3. How can a measurement system be integrated into an existing bicycle component in a product-credible way?

1.3 Thesis outline

The thesis is structured as a progressive journey from theoretical framing to experimental validation and product-oriented reflection. Chapter 1 establishes the research context through a structured review of the state of the art, addressing hydration and carbohydrate intake in endurance cycling, physiological performance limits, performance metrics, and existing monitoring and data analysis platforms. This chapter highlights the gap between the relevance of in-activity nutrition and the current lack of direct, continuous measurement tools.

Building on this foundation, Chapter 2 translates the identified research gap into a design engineering brief. It defines the target users and use scenarios, explores alternative system architectures, and formalizes the technical and design requirements that guide the development of the project.

Chapter 3 constitutes the real core of my thesis and focuses on prototyping and system development. It documents the iterative design, calibration, and testing of two prototypes: an initial functional prototype aimed at validating the measurement principle under controlled and quasi-real conditions, and a second, more integrated prototype oriented toward product-level constraints such as aerodynamics, integration, and form. Static tests, quasi-real setups, and on-bike experiments are used to evaluate performance, limitations, and design trade-offs.

Finally, Chapter 4 synthesizes the results. The chapter discusses the main outcomes of the work, reflects on the limitations encountered, and outlines future development directions, positioning the project within a broader ecosystem that connects product design, performance analysis, and data-driven approaches in high-performance cycling.

1.4 Thesis aim within design engineering

Within the field of design engineering, this thesis aims to demonstrate how measurement, data, and physical product design can converge into a single system capable of generating new forms of performance-related knowledge. Rather than optimizing an existing component, the project explores how an everyday object—the bottle cage—can be reinterpreted as an active sensing interface between the athlete and their physiological inputs.

I would like to underline that the objective is not to deliver a finalized commercial product, but to validate the feasibility of a measurement-driven design approach, where technical accuracy, system integration, and product credibility are addressed simultaneously. In this sense, the thesis positions design engineering as a mediating discipline between physiology, electronics, and industrial design, capable of transforming abstract performance needs into tangible, testable artifacts.

2.0 Context

2.1 High-performance cycling and the marginal gains paradigm

Elite professional cycling represents one of the most advanced examples of performance-optimized endurance sport. Within the WorldTour circuit, athletes compete in an environment characterized by extremely homogeneous levels of physical preparation, technical skill, and tactical competence. As a result, the margins that separate riders competing for victory from those finishing outside the points are increasingly small. In such a context, competitive outcomes rarely depend on a single dominant factor, but rather emerge from the interaction of multiple variables, each contributing a limited yet potentially decisive effect on overall performance (Coyle, 2005; Hawley & Noakes, 1992).

Within this environment, the marginal gains paradigm has progressively established itself as a guiding framework for performance optimization. According to this paradigm, improvements in overall performance arise from the accumulation of numerous small, incremental enhancements obtained through the systematic optimization of each component of the athlete–bicycle system (Burke, 2014). Once a high level of performance maturity has been reached, competitive advantage is no longer achieved through radical interventions, but through the continuous reduction of inefficiencies. Even seemingly negligible improvements, when combined and sustained over time, can result in meaningful differences in competitive outcomes.

The adoption of the marginal gains approach has profoundly influenced the evolution of professional cycling, extending across heterogeneous domains such as equipment design, aerodynamics, biomechanics, training methodology, and race strategy (Foster et al., 2017). Performance is no longer interpreted as the expression of a single physiological capacity, but rather as the outcome of a complex balance between physical, technical, and decision-making factors. Cycling can therefore be understood as an integrated system, in which every design choice and strategic decision contributes to defining the final performance output.

A central component of this system is energy management during exercise. The ability to sustain high power outputs over time, recover effectively between repeated efforts, and delay the onset of fatigue represents one of the primary determinants of endurance performance (Jeukendrup & Killer, 2010). In this sense, energetic efficiency depends not only on the athlete's physiological capabilities, but also on the management of the inputs that fuel the system, including training load, recovery strategies, and nutrition.

The marginal gains paradigm also implies a fundamental transformation in the role of data within decision-making processes. Objective measurement of performance-related variables is not valuable per se, but becomes meaningful insofar as it supports informed decisions in training planning, tactical execution, and performance management (Halson, 2014). Performance is therefore interpreted as a dynamic and multifactorial phenomenon, requiring conceptual and analytical tools capable of integrating information across different domains rather than relying on a single metric.

Even from the beginning we can see that professional cycling can be described as a complex adaptive system, in which performance emerges from the interaction between physiological inputs, gear choices (Figure 1), environmental conditions, and tactical choices (Newell, 1986). Optimizing such a system requires the ability to identify, measure, and manage variables that are not always immediately visible or easily quantifiable. This requirement highlights the limitations of current performance analysis approaches and motivates the extension of the marginal gains paradigm toward less explored dimensions, including the management and measurement of nutritional inputs during exercise.

Brand	Model (Click for full review)	Year	Tire Type	Inner Tube	Price Range	Buy At	Width	Weight	RR Med	RR High
Search Brand or Model..							Specified / Measured mm	Specified / Measured Grams	Watts	Watts
Vittoria	Corsa Pro Speed TLR 28	2024	TLR	None	High+		28 / 28	250 / 240	Pro	**6.7**
Vittoria	Corsa Pro Speed TLR WR 29	2025	TLR	None	High+		29 / 27	255 / 250	Pro	**7.0**
Vittoria	Corsa Pro Speed TLR WR (on 22/23 mm rims) 29	2025	TLR	None	High+		29 / 29	255 / 250	Pro	**7.4**
Veloflex	Record TLR 25	2023	TLR	None	High+		25 / 26	175 / 170	Pro	**7.7**
Continental	Archetype 30	2025	TLR	None	High+		30 / 30	275 / 271	Pro	**8.0**
Vittoria	Corsa Speed G+ 2.0 (TLR) 25	2019	TLR	None	High		25 / 27	240 / 227	Pro	**8.3**
Continental	Grand Prix 5000 TT TR 28	2023	TLR	None	High+		28 / 29	245 / 250	Pro	**8.3**
Continental	Grand Prix 5000 TT TR (TdF) 25	2022	TLR	None	High+		25 / 26	215 / 210	Pro	**8.4**
Schwalbe	Pro One TT TLE Addix 25	2020	TLR	None	High		25 / 27	205 / 222	Pro	**9.0**
Vittoria	Corsa Speed G+ 1.0 (TLR) 23	2016	TLR	None	High		23 / 25	205 / 225	Pro	**9.2**
Enve	SES Raceday 29	2024	TLR	None	High+		29 / 30	210 / 214	Pro	**9.3**

Figure 1: Road Bike Rolling Resistance Comparison - BireRollingResistance.com - 2026

2.2 Physiological determinants of endurance performance

Endurance performance in professional cycling results from the interaction of multiple physiological determinants governing energy production, utilization, and maintenance during prolonged exercise. Unlike sports characterized by short, maximal efforts, cycling requires the ability to sustain high levels of mechanical work over extended periods, often under variable environmental conditions and with repeated fluctuations in intensity. In this context, performance depends largely on the efficiency of the body's energy systems and on the ability to delay fatigue onset (Hawley & Stepto, 2001).

From a metabolic standpoint, energy production during endurance exercise is primarily supported by the oxidation of carbohydrates and lipids, with their relative contribution varying according to exercise intensity and duration. As intensity increases, carbohydrate metabolism becomes progressively more dominant, as it allows for faster ATP production compared to fat oxidation (Romijn et al., 1993). In the competitive context of professional cycling—characterized by sustained moderate-to-high intensities and frequent changes in pace—the availability of carbohydrates therefore represents a critical factor for maintaining performance.

One of the main physiological limitations to endurance performance is the depletion of glycogen stores, both muscular and hepatic. A substantial body of research has shown that glycogen depletion is closely associated with the onset of fatigue and with a reduction in the capacity to sustain high power outputs (Bergström et al., 1967; Coyle et al., 1986). Performance is thus constrained not only by cardiovascular or muscular capacity, but also by the availability of sufficient energetic substrates to support the required workload.

To mitigate these limitations, carbohydrate ingestion during exercise has become a well-established practice in endurance sports. The intake of exogenous carbohydrates helps preserve endogenous glycogen stores, maintain blood glucose levels, and stabilize metabolic responses throughout prolonged effort (Jeukendrup, 2014). However, the body's capacity to absorb and utilize carbohydrates during exercise is not unlimited and constitutes one of the primary physiological bottlenecks of endurance performance.

Carbohydrate absorption at the intestinal level is mediated by specific transporters, whose maximum transport capacity determines the amount of carbohydrate that can be effectively utilized per unit of time. This physiological constraint implies that beyond a certain intake threshold, additional carbohydrates do not translate into increased energy availability and may instead lead to gastrointestinal disturbances (Jeukendrup & Moseley, 2010). Nutritional intake therefore becomes an optimization problem, in which quantity, composition, and timing must be carefully calibrated.

Within this framework, liquid carbohydrate intake is of particular interest. Carbohydrates dissolved in solution enable faster gastric emptying and absorption compared to solid forms, while allowing fine modulation of energy supply during exercise (Jeukendrup, 2011). Moreover, liquid intake enables the simultaneous provision of carbohydrates and electrolytes, supporting fluid balance and neuromuscular function during prolonged effort.

In professional cycling, where performance is often determined by the ability to repeatedly sustain high-intensity efforts over time, the management of energetic input during activity assumes a central role. Nutrition can no longer be considered an ancillary or standardized component, but rather a true performance variable whose optimization requires a detailed understanding of the underlying physiological mechanisms (Burke et al., 2011).

Despite the well-established physiological knowledge in this area, its translation into operational strategies is still largely based on theoretical models or generalized protocols. The lack of objective data on actual carbohydrate and fluid intake during exercise limits the ability to rigorously evaluate the effectiveness of nutritional strategies and adapt them to individual athlete characteristics. This discrepancy between physiological understanding and measurement capability represents one of the critical gaps in the optimization of endurance performance.

2.3 Hydration redefined: from water balance to liquid energy intake

In an endurance sports, hydration has traditionally been associated with the maintenance of body water balance and the prevention of dehydration. Within this conventional perspective, fluid intake during exercise has been primarily interpreted as a means to compensate for sweat losses and to support thermoregulation mechanisms (Sawka et al., 2007). While these aspects remain fundamental, an exclusively water-centered interpretation of hydration is no longer sufficient to describe the role that fluid intake plays in high-level performance.
In professional cycling, hydration assumes a more articulated dimension that extends beyond fluid balance and becomes directly intertwined with energy management and electrolyte regulation. Fluids ingested during exercise represent the primary vehicle through which athletes introduce not only water, but also carbohydrates and electrolytes—elements that are essential for sustaining prolonged effort and maintaining neuromuscular function (Maughan & Shirreffs, 2010). From this perspective, hydration can be reinterpreted as a multifactorial physiological input, in which different components contribute in an integrated manner to performance.

Fluids used in endurance cycling can be classified into several categories, each characterized by specific physiological and performance-related functions. Plain water represents the simplest form of hydration and plays a crucial role in maintaining plasma volume and facilitating heat dissipation. However, when consumed as the sole fluid source during prolonged exercise, water alone is insufficient to support metabolic demands and may contribute to the dilution of plasma electrolyte concentration (Noakes, 2012).
Alongside water, electrolyte-containing beverages—particularly those providing sodium, potassium, and chloride—play a central role. Electrolyte losses through sweating can negatively affect neuromuscular function, perceived exertion, and the ability to sustain power output over time. The ingestion of electrolyte solutions supports osmotic balance and improves fluid retention, thereby reducing the risk of cramps and functional disturbances during prolonged exercise (Shirreffs & Sawka, 2011).

Another important category is represented by isotonic beverages, which are formulated to present a solute concentration similar to that of body fluids. These solutions aim to optimize gastric emptying and intestinal absorption, enabling the simultaneous delivery of fluids and energy while minimizing gastrointestinal stress (Jeukendrup & Gleeson, 2019). Hypotonic beverages, characterized by a lower solute concentration, are instead used in situations where rapid rehydration is prioritized, such as in hot environmental conditions or during moderate-intensity exercise phases.

Conversely, hypertonic beverages, which contain a higher solute concentration than body fluids, present significant limitations when consumed during exercise. Their intake can slow gastric emptying and increase the risk of gastrointestinal discomfort, making their use during activity generally limited or carefully modulated according to specific conditions and individual tolerance (Rehrer, 2001).
In professional cycling, the selection of fluid type and its modulation throughout activity therefore constitute a strategic component of effort management. Fluid composition, intake volume, and timing directly influence energy availability, electrolyte balance, and the capacity to sustain the intensity demands of competition. Hydration thus becomes a dynamic interface between the athlete and the physiological system, through which multiple performance determinants are regulated simultaneously.

Despite this complexity, hydration in professional cycling is still often managed through standardized protocols based on fixed volumes or rigid timing schemes. Such approaches rarely account for individual variability between athletes, changes in environmental conditions, or the specific dynamics of racing and training. Moreover, the absence of objective measurements of actual fluid intake makes it difficult to evaluate the effectiveness of different beverage formulations and to compare their impact on performance in a rigorous manner.

My need emerges to move beyond a simplified view of hydration and to consider liquid intake as a full performance variable. Optimizing this variable requires not only physiological understanding, but also the ability to directly and continuously measure functional fluid intake during exercise. The possibility of capturing this data represents a key step toward extending the marginal gains paradigm into a physiological dimension that remains underexplored, laying the groundwork for more informed and performance-oriented nutritional strategies.

2.4 Carbohydrate intake as a physiological bottleneck

Carbohydrate availability during exercise is widely recognized as one of the main physiological constraints on the ability to sustain high intensities over time. Compared to lipids—whose energy stores are large but whose oxidation rate is slower—carbohydrates support faster ATP production and become decisive when intensity is moderate-to-high or when racing requires repeated changes of pace (Jeukendrup, 2014; Romijn et al., 1993). In competitive scenarios, performance therefore depends not only on endogenous glycogen stores, but also on the athlete's ability to ingest exogenous carbohydrates in a way that is effective, continuous, and tolerable.

A central limiting factor is intestinal absorption capacity. Carbohydrate intake during exercise is not simply a quantitative choice ("how much to take"), but a transport problem with an upper throughput. For glucose and glucose-like carbohydrates (including maltodextrin, which is rapidly converted), absorption is primarily mediated by the intestinal transporter SGLT1, which tends to saturate around ~1 g/min, corresponding to roughly 60 g/h when using a single carbohydrate source (Jeukendrup, 2010). Beyond this point, increasing intake does not automatically increase the amount of carbohydrate that becomes available for muscular work.
This absorption ceiling also explains why indiscriminately increasing carbohydrate intake can become counterproductive. When absorption capacity is exceeded, a growing fraction of carbohydrates remains in the intestinal lumen, increasing osmotic load and raising the likelihood of gastrointestinal (GI) symptoms. In practical terms, GI discomfort does not only affect well-being; it can directly impair performance by forcing athletes to reduce intake, change strategy, or even interrupt nutritional execution during critical moments (Jeukendrup, 2017).
One of the most robust strategies to push beyond the ~60 g/h ceiling is the use of multiple transportable carbohydrates, typically combining a glucose-like source with fructose to exploit different transport pathways (SGLT1 for glucose/maltodextrin and GLUT5 for fructose). Under controlled experimental conditions, this approach has been shown to increase exogenous carbohydrate oxidation rates up to ~1.75 g/min (≈ 100–105 g/h), (Figure 2), clearly above the single-transporter ceiling (Jeukendrup, 2010). From an applied standpoint, this evidence has informed recommendations suggesting that, during prolonged endurance events, athletes may target 60–90 g/h—and in some cases more—often using specific blends (commonly reported ratios around 2:1 glucose-like to fructose) (Thomas et al., 2016).

However, these values should be interpreted as physiological reference ranges rather than guarantees. They are derived under controlled conditions and require a practical ability to implement intake during exercise—something that is often harder than the literature can make it seem.

In World Tour cycling, a common tool to reach high carbohydrate targets is the use of energy gels, which deliver concentrated carbohydrate doses in small volumes and can be consumed even during high-intensity phases (climbs, attacks, finales). A single gel typically provides roughly 20–40 g of carbohydrates, allowing athletes to structure intake through discrete events distributed over time (Burke et al., 2011). Yet gels introduce constraints that reinforce the idea of carbohydrate intake as a true bottleneck.
First, because gels are highly concentrated, they often increase gastric osmotic load and therefore benefit from concurrent water intake to support gastric emptying and reduce GI discomfort—an operational requirement that is not always easy to satisfy in racing conditions (Jeukendrup, 2017). Second, gels are typically ingested as "events", while metabolic demand is continuous and dynamic. This mismatch can create temporal misalignment between availability and demand, especially when race dynamics disrupt planned timing.

A third issue is real-world compliance. On paper, an athlete "should" ingest a target amount per hour. In reality, intensity, positioning, stress, accessibility of bottles, and the onset of nausea or GI symptoms often cause substantial deviations from the theoretical plan. As a result, the amount of carbohydrate actually ingested—and effectively absorbed—may differ significantly from what was planned, precisely when intake is most needed.
Within this context, gastrointestinal tolerance becomes a decisive performance variable. Importantly, tolerance is not fixed: it can be improved through repeated exposure to race-like intake strategies in training ("gut training"), increasing the likelihood that high intake targets are practically sustainable (Jeukendrup, 2017). Even with adaptation, however, GI response remains strongly individual and context-dependent.

A major limitation of current practice is the lack of tools capable of verifying, in real time, the downstream effect of intake—particularly GI consequences—and relating it immediately to performance. Most evaluations remain retrospective and indirect (overall performance outcomes, subjective perception, symptom reporting). What is missing is the ability to observe, with temporal resolution, how intake influences the capacity to hold power, respond to pace changes, or maintain intensity near critical domains.
From a performance standpoint, the ergogenic effect of carbohydrate intake is not limited to avoiding dramatic "bonking". It can be reflected in measurable improvements in the ability to sustain work over time. Evidence shows that carbohydrate ingestion during prolonged exercise can improve endurance performance and/or time-to-exhaustion compared to low or no carbohydrate conditions, with effects commonly reported in the range of a few percentage points depending on protocol and context (Jeukendrup, 2014; Thomas et al., 2016). In elite racing, such differences are small in absolute terms but potentially decisive when margins are minimal.

To interpret these differences rigorously, it is useful to clarify the concepts of threshold and intensity zones in cycling. In applied performance practice, threshold is often operationalized as Functional Threshold Power (FTP)—commonly defined as the highest mean power a rider can sustain for a prolonged period (frequently approximated using test protocols such as 20-minute efforts) (Allen & Coggan, 2010). Physiologically, this concept relates to constructs such as the second lactate threshold (LT2) or the maximal lactate steady state (MLSS), representing the transition beyond which metabolic disturbance increases rapidly and sustainable duration decreases (Faude et al., 2009).

Power-based zone models (often 6–7 zones) define intensity bands as percentages of FTP, spanning low-intensity endurance, tempo, threshold, and above-threshold domains (e.g., VO_2max and anaerobic work) (Allen & Coggan, 2010). Within this framework, seemingly small absolute differences—on the order of a few watts—can meaningfully change how deep an athlete is operating within a given domain, with direct implications for fatigue accumulation and sustainable duration. In other words, 5–10 W can be negligible at maximal power, but highly meaningful near threshold because it can shift the effort from “manageable” to “rapidly degrading” (Faude et al., 2009).
Heart-rate-based zones are also widely used and can be informative for internal load monitoring. However, heart rate responds with a delay to intensity changes and is influenced by external and physiological factors such as heat, dehydration, fatigue, and cardiovascular drift during prolonged exercise (Coyle & González-Alonso, 2001).

Connecting these concepts to carbohydrate intake clarifies why modest differences in sustainable power can matter: adequate carbohydrate availability does not “add watts” in a simple way, but helps stabilize output near critical intensity domains, reducing the probability of crossing into a zone where sustainable duration collapses.

In racing, this stability can be the difference between holding a wheel, responding to an acceleration, or maintaining a climbing pace without a rapid performance drop (Jeukendrup, 2014).

Figure 2: Ex. of 1 hour of fuel (130 gr of carbohydrates) during a race -Maurten.com - 2026

A practical example makes this concrete. Consider an athlete with an FTP of 320 W. Riding at 300–310 W corresponds to ~94–97% of FTP, typically near high-tempo or the transition toward threshold. An increase of 5–10 W to 315–320 W moves the rider closer to, or directly into, threshold intensity, where metabolic disturbance rises and sustainable duration can drop sharply (Allen & Coggan, 2010; Faude et al., 2009). In a selective climb or a late-race effort, the ability to sustain this slightly higher power—or to prevent a decline of the same magnitude—can meaningfully affect positioning and outcome. The same situation can be described in heart-rate terms, but heart rate will often lag and drift, making it less reliable for capturing rapid transitions in real time (Coyle & González-Alonso, 2001).
Seen through a marginal gains lens, the absence of objective feedback on actual intake becomes a relevant limitation: without direct measurement, nutrition remains a partially opaque variable within current performance analysis models. Carbohydrate intake is therefore not only a physiological bottleneck—it is also a measurement bottleneck, difficult to observe with temporal precision and difficult to integrate rigorously into data-driven performance workflows. This gap—between strong physiological knowledge and limited real-time observability—is exactly where the design opportunity explored in this thesis is positioned.

2 5 Current methods for monitoring hydration and nutrition in cycling

Despite the well-established role of hydration and carbohydrate intake in endurance performance, the methods used to monitor these inputs in cycling remain limited and largely indirect. Unlike variables such as power output or heart rate—both of which can be measured continuously and with high temporal resolution during exercise—fluid and nutrient intake are rarely captured as objective data. In most cases, intake is estimated, reconstructed retrospectively, or assumed to follow a predefined plan rather than being directly measured in real time (Jeukendrup, 2017).

One of the most common approaches to assess hydration status is the measurement of body mass change before and after exercise. This method is based on the assumption that variations in body mass primarily reflect fluid losses due to sweating. While useful for obtaining a coarse estimate of overall fluid balance, body mass change provides limited insight from a performance perspective. It offers no information on intake timing, fluid composition, or distribution throughout the activity, making it impossible to relate hydration behavior to specific phases of effort or variations in mechanical output (Sawka et al., 2007).

In professional and semi-professional cycling, hydration and nutrition are more often managed through prescriptive nutritional protocols defined in advance based on expected duration, estimated intensity, and environmental conditions.

These protocols typically specify target fluid volumes, carbohydrate intake rates, and the frequency of gel or drink consumption. While such plans are essential planning tools, they implicitly assume full athlete compliance. In real racing conditions, however, the gap between theoretical plans and actual execution can be substantial—especially during high-intensity phases or under competitive stress. Without direct measurement, it is impossible to verify whether, when, and to what extent these plans are effectively followed (Burke et al., 2011).

In other contexts, intake is assessed through self-reporting, post-activity recall, or subjective estimates. These approaches introduce significant variability related to cognitive, perceptual, and memory-related factors, severely limiting their reliability. In prolonged or high-intensity activities typical of endurance cycling, athletes' ability to accurately recall intake quantity and timing is particularly compromised, making such tools unsuitable for rigorous quantitative analysis or systematic comparison of nutritional strategies (Maughan & Shirreffs, 2010).
A common limitation across all these approaches is the absence of continuous, real-time measurement of fluid and nutrient intake. Current practices do not allow hydration and nutrition to be integrated into performance analysis frameworks that rely on temporally resolved data. As a result, it is not possible to observe how changes in intake are immediately reflected in power output, intensity distribution, or physiological response during exercise. This creates a marked informational asymmetry between the richness of data available for mechanical output and the scarcity of data describing one of the most relevant physiological inputs (Halson, 2014).

The consequences of this gap become particularly evident in performance analysis approaches focused on intervals and short-term intensity fluctuations. Without objective intake data, variations in performance that cannot be directly attributed to training load or fitness status are difficult to interpret. Similarly, comparing different nutritional strategies or evaluating targeted interventions becomes methodologically weak when intake remains unobserved.

Overall, current methods for monitoring hydration and nutrition in cycling are adequate for general or retrospective assessment, but insufficient to support advanced, optimization-oriented performance analysis. The lack of tools capable of directly, continuously, and objectively measuring fluid intake during exercise constitutes a structural limitation of the current performance analysis ecosystem. Given the evidence discussed in previous sections—identifying carbohydrate intake as a critical and potentially decisive performance factor—this methodological gap emerges as a key area for intervention.

Some widely used cycling devices, such as Garmin Edge head units, have introduced features aimed at supporting hydration management during activity.

Among these, one of the most common is the drink reminder, a notification prompting the athlete to drink at regular or adaptive time intervals. In more recent models, reminder frequency can be adjusted based on estimated activity duration, intensity, and, in some cases, environmental factors such as temperature (Garmin, 2023).

It is important to clarify that such features do not measure fluid intake. Drink reminders do not record whether the athlete actually drinks, nor the quantity ingested. They simply prompt an action based on a temporal or predictive model. Similarly, some associated platforms provide post-activity estimates of fluid loss or intake by combining parameters such as exercise duration, estimated workload, and environmental data. These outputs produce aggregated estimates, but offer no information on actual intake timing, frequency, or fluid composition (Casa et al., 2010).

Now we can see that this approach presents structural limitations. The information provided is model-based rather than experimentally measured, and therefore difficult to integrate rigorously with key variables such as power output, interval distribution, or physiological response over time. Without direct measurement, it is impossible to determine whether a change in performance is associated with a specific intake event or whether reminders had any behavioral effect on the athlete at all.
A further limitation is the absence of a structured temporal log of intake. Current systems do not track how much the athlete drinks, at which moment during the activity, or under which performance and environmental conditions. Consequently, there is no intake timeline that can be overlaid with power, heart rate, or elevation data to analyze the effect of hydration during specific effort phases. This makes it impossible, for example, to evaluate whether fluid intake preceding a climb or a high-intensity segment contributed to power stabilization or delayed performance decline.

I will say that these features create a perception of hydration control without providing true observability of the phenomenon. Hydration appears to be "managed" because it is prompted or estimated, yet it remains an unmeasured, unverifiable variable that cannot be robustly integrated into data-driven performance models used in high-level cycling. Predictive algorithms may offer general support, but they do not replace the need for objective experimental data—especially when the goal is to correlate fluid intake with performance outcomes within a marginal gains framework.

Current implementations represent an initial step toward recognizing the importance of hydration, while simultaneously highlighting the limitations of an approach based on reminders and estimates rather than direct measurement. This mismatch between acknowledged physiological relevance and actual measurement capability constitutes one of the key methodological gaps addressed by the present thesis. It is precisely from this asymmetry—between critical physiological inputs and limited observability—that the subsequent phase of this work emerges, focused on defining a design brief capable of integrating direct fluid intake measurement within the athlete–bicycle system, while remaining consistent with real-world performance dynamics and data-driven cycling practice.

2.6 Existing products and technological approaches

From my experience and my research i saw in the recent years, a variety of products and technological approaches have emerged with the aim of supporting hydration and, more broadly, intake management during exercise. When examined critically, however, most existing solutions can be grouped into categories that either estimate or infer hydration-related needs, or treat intake primarily as a behavior to be remembered rather than as a variable to be directly measured and integrated with performance data in real time. This section reviews the main families of existing solutions, highlighting representative examples and their limitations with respect to high-performance cycling.

A first category includes algorithm-based reminder and estimation systems, typically integrated into mainstream cycling computers and software platforms. As discussed in Section 1.5, a direct example is provided by the “Smart Eat and Drink Alerts” implemented in Garmin Edge devices. These features generate adaptive reminders for drinking or eating, based on variables such as activity duration, estimated intensity, elevation, temperature, and—when available—heart rate and power data (Garmin, 2023).
While useful as operational support, this approach remains fundamentally predictive. The system does not verify whether the action actually occurred, does not measure the quantity ingested, and does not generate a structured, interoperable temporal log of intake. Consequently, the output is difficult to correlate rigorously with performance dynamics such as power fluctuations or interval structure. Intake remains a modeled assumption rather than an experimentally observed variable (Jeukendrup, 2017).

A second category is represented by consumer-oriented smart bottles designed to track daily water intake and support habit formation. A well-known example is HidrateSpark, which markets bottles capable of tracking water consumption, synchronizing with a mobile application, and providing visual reminders directly on the bottle itself.

These products are effective in a lifestyle or wellness context, but show clear limitations when translated to competitive cycling:

- they focus almost exclusively on water intake and daily targets;
- they are not designed around the high-intensity interaction between bottle, bottle cage, and bicycle;
- they offer limited integration with performance metrics relevant to interval-based analysis.

Although such devices may “track” intake in a general sense, they do not address intake as a performance variable within real cycling conditions (Maughan & Shirreffs, 2010).

A third family includes sweat sensors and hydration biosensors, which do not measure what the athlete drinks, but instead attempt to quantify fluid loss—often including sweat rate and electrolyte concentration—to generate personalized recommendations. Examples include the Nix Hydration Biosensor, described as a system that continuously measures fluid and electrolyte losses and provides real-time insights on when, what, and how much to drink, as well as the Epicore Biosystems Gx Sweat Patch, a wearable microfluidic sensor designed to assess sweat rate and chloride concentration.

These approaches are particularly relevant because they move closer to physiological measurement. However, with respect to the objective of this thesis, they present two key limitations:

- they measure a proxy (loss) rather than the actual intake;
- they translate physiological signals into recommendations that remain model-based and are not directly integrable as input variables alongside power or interval data.

Moreover, the localized nature of sweat measurements raises questions about representativeness and robustness in real-world racing conditions (Baker et al., 2018).
A broader and more transversal area concerns the recent expansion of non-invasive wearable sensing technologies—including sweat, respiration, and temperature monitoring—within elite and marginal-gains-oriented environments. Industry reports and applied research highlight growing interest in these technologies, alongside challenges related to data access, regulatory constraints, integration, and interpretation in professional contexts. Despite their potential, the focus of these systems remains largely on “measuring the body” rather than on recording the objective action of drinking, in terms of quantity, timing, and performance context (Halson, 2014).

Overall, the state of the art reveals a rich but fragmented landscape. Existing solutions either:

(a) estimate and remind (cycling computers),
(b) track habits (user input on softwares), or
(c) infer needs from indirect physiological proxies (sweat sensors).

What is missing is a system capable of producing a simple, experimental, and operational dataset: a temporal log of actual intake—how much and when the athlete drinks, and ideally what type of fluid—directly integrable with power, heart rate, and elevation data.
This absence is particularly limiting in data-driven cycling, as it prevents robust correlations between implemented nutritional strategies and performance dynamics. The benchmark therefore confirms the presence of a clear design gap between the recognized physiological importance of hydration and current measurement capabilities in high-level cycling. It is precisely within this gap—between algorithmic recommendations and experimental observation of intake—that the design opportunity addressed in this thesis is positioned.

2.7 Synthesis of gaps and design requirements

The analysis presented in the previous sections highlights a structural mismatch between the recognized physiological importance of hydration and carbohydrate intake in cycling performance and the current ability to measure and integrate these inputs within performance analysis systems. While scientific literature consistently identifies carbohydrate availability as a key limiting factor in the ability to sustain high intensities over time, and while advanced tools exist to continuously monitor mechanical output and physiological response, actual fluid intake remains largely unobserved during exercise (Jeukendrup, 2014).
The reviewed methods and products show that hydration is currently addressed primarily through indirect approaches.

On one hand, algorithm-based systems and reminders suggest when to drink or estimate fluid needs based on predictive models. On the other, physiological sensors quantify proxies such as sweat rate or electrolyte loss. In both cases, the data produced do not represent an experimental measurement of the act of drinking, but rather inferred or prescriptive information. This creates a significant gap between what is planned or estimated and what the athlete actually ingests during effort.

From a performance analysis perspective, the absence of direct intake measurement constitutes a relevant methodological limitation. Data-driven models used in elite cycling rely on high-resolution time series describing effort dynamics through variables such as power, heart rate, and elevation.
The lack of an equivalent time-resolved dataset for fluid intake prevents robust correlations between intake behavior and performance variations, responses to intensity intervals, or the ability to sustain power near threshold. As a result, hydration and nutrition remain external variables to the analytical system, despite their well-established role in determining performance outcomes.

The synthesis of the state of the art therefore reveals several key gaps, which can be summarized as follows:

- absence of direct and objective measurement of fluid intake during cycling activity;
- lack of a continuous temporal log describing how much and when the athlete drinks;
- inability to natively integrate intake data with performance parameters already collected;
- strong dependence on algorithmic estimates or physiological proxies rather than experimentally verified data;
- limited alignment of existing solutions with the real dynamics of the cycling gesture, particularly under high-intensity conditions.

Based on these gaps, a set of design requirements emerges clearly and defines the intervention space of this thesis. First, the system must be capable of directly measuring actual fluid intake, without relying on estimation or inference. This measurement must generate a continuous time series, allowing synchronization with power, heart rate, and elevation data.
A second fundamental requirement concerns integration with the bicycle and with the athlete's habitual gesture. The system should be positioned within an interface that is already part of the cyclist's routine interaction with the bike, avoiding behavioral modifications that could alter performance or compromise data validity. Measurement must occur transparently, without interfering with riding, bottle access, or race dynamics.

The data produced must be compatible with the existing digital ecosystem used in cycling performance analysis, enabling export, synchronization, and joint interpretation with established performance metrics. Only under these conditions can fluid intake become a truly analyzable variable within performance models, allowing exploration of relationships between intake, physiological response, and effort sustainability near critical intensity domains.
Finally, this synthesis highlights that the value of the proposed system does not lie solely in the act of measurement, but in the conceptual transformation of hydration from an estimated variable into an observable one. Within a marginal gains framework, this shift enables new opportunities for personalized nutritional strategies, experimental validation of intake protocols, and more accurate interpretation of performance variability across training and competition contexts.
These requirements define the framework for the next phase of this work, which focuses on the conceptual design of the system and on the definition of a project brief capable of translating the identified gaps into coherent technical and design solutions, aligned with the constraints and realities of high-performance

3.0 Concept Development and System Definition

3.1 From research gap to design question

As we saw in the Chapter 1, in high-level cycling, hydration and carbohydrate intake represent physiologically decisive factors for performance, while remaining largely excluded from the measurement and analysis systems routinely used in practice. Despite the availability of high-resolution data describing mechanical output and physiological response, actual fluid intake is still managed mainly through estimates, predictive models, or prescriptive protocols rather than being directly observed during exercise.

Within a data-driven performance ecosystem, performance is described as a continuous temporal sequence of measurable events, whereas one of the most relevant energetic inputs remains substantially unobserved. This discrepancy does not stem from a lack of awareness of the importance of nutrition, but rather from the intrinsic complexity of the act of drinking while cycling. Fluid intake occurs under dynamic conditions, often at high intensity, and does not allow for explicit measurement procedures or additional interactions without altering the athlete's behavior. As a result, hydration is currently treated as a variable to be estimated or prescribed, rather than as an experimental datum acquired during performance.
From a performance analysis perspective, this situation introduces a significant methodological limitation. The possibility of rigorously correlating power output, interval distribution, and effort sustainability with implemented nutritional strategies is strongly reduced when actual intake is not measured. In particular, the absence of a continuous temporal record of fluid intake makes it difficult to interpret performance variations that cannot be explained solely by training load or fitness status.

When I reframed from a design perspective, this problem can be understood as an issue of system integration. Rather than adding another layer of estimation or behavioral support, the challenge lies in making an opaque phenomenon observable by embedding measurement directly within the athlete–bicycle system. A key principle emerges from this reframing: non-interference with the sporting gesture. Any solution requiring a change in athlete behavior risks compromising both data validity and performance quality.

This approach also reflects a consideration rooted in the author's direct experience within cycling and performance analysis contexts. The increasing availability of data does not automatically lead to better understanding if critical variables remain unmeasured.

On the contrary, the absence of a fundamental input such as fluid intake can lead to partial or misleading interpretations of performance, especially within a marginal gains framework, where small differences carry significant weight. From this standpoint, the value of a measurement system does not lie in technological complexity, but in its ability to render a critical aspect of athletic behavior observable without altering it.

Based on these considerations, the design problem guiding this thesis can be formulated as follows:

How can real fluid intake be measured during high-performance road cycling, in real-world conditions, without altering the athlete's behavior and while remaining compatible with existing performance analysis workflows?

This design question defines the conceptual perimeter of the project and establishes the criteria guiding subsequent decisions: centrality of the sporting gesture, necessity of direct and continuous measurement, and integration of intake data within the data-driven performance ecosystem. Starting from this question, Chapter 2 develops the design process leading from user and context definition to the formulation of a coherent project brief and system architecture aligned with the objectives identified.

3.2 User definition and system stakeholders

The definition of the reference user for the system was not addressed as an intuitive or preliminary choice, but as the outcome of an analytical process directly derived from the objectives identified in Chapter 1. Since the core problem concerns the lack of an objective and integrable measurement of fluid intake during cycling activity, user definition was guided not by who physically interacts with the device, but by who ultimately uses the generated data to interpret and optimize performance.

Within this framework, the primary user of the system is identified as the performance engineer and the strength and conditioning coach operating within a professional road cycling team. This choice reflects the central role these figures play in performance-related decision-making processes. Their work is based on the systematic analysis of objective data collected during training and competition, with the goal of interpreting athlete behavior, evaluating the effectiveness of implemented strategies, and planning targeted interventions. Within these workflows, the availability of a new measurable variable—actual fluid intake—represents a relevant informational asset, as it fills a gap that is currently present in performance analysis models.

From the perspective of the performance engineer, intake data does not have value as an isolated metric, but as a variable to be correlated with existing parameters such as power output, intensity distribution, and effort sustainability near threshold. The selection of this profile as the primary user therefore reflects the need to ensure that the system produces reliable, structured, and interoperable data, rather than immediate feedback aimed at the athlete. In other words, the main value of the system is assumed to emerge after the activity, during post-exercise analysis and interpretation.

The professional athlete is identified as the direct user of the system, but not as its primary user. This distinction is fundamental to understanding the adopted design approach. Although the athlete physically interacts with the product during activity, they are neither the main recipient of the generated data nor the decision-maker who determines its strategic use. From a design standpoint, the athlete is part of the system being measured and must be monitored without being actively involved in the data acquisition process. This assumption follows directly from the constraint, identified in Chapter 1, of avoiding any alteration of the sporting gesture or additional cognitive load during performance.
The decision not to consider the athlete as the primary user is also grounded in a critical assessment of real use conditions. During racing or high-intensity training, athletes operate under significant physical and cognitive stress, making any additional conscious interaction with the system inappropriate. Even minimal attention demands could compromise performance or introduce confounding variables into the collected data. Consequently, the project assumes that the system must function completely transparently for the athlete, without modifying habits, gestures, or tactical behavior.

Alongside these two main roles, the system involves a set of secondary stakeholders who contribute to data interpretation and decision-making. These include sports nutritionists, data analysts, and technical staff within the team. Operating at different levels of the decision-making chain, these stakeholders use data to validate nutritional strategies, compare individual responses, and adapt intake protocols based on environmental conditions and athlete-specific characteristics. The system is therefore conceived as part of a broader decision-making ecosystem, in which intake data supports evaluation and optimization rather than acting as an end in itself.

The decision to focus the project on a professional, high-performance context results from a comparative evaluation of alternative use scenarios. In consumer or amateur contexts, hydration is often treated as an issue of awareness or behavioral adherence, and existing solutions tend to emphasize reminders, gamification, or simplified feedback. In contrast, in professional cycling the value of data lies in its accuracy, repeatability, and suitability for comparative and longitudinal analysis. This thesis deliberately positions itself within this latter domain, assuming that the reference user already possesses the expertise and analytical tools required to interpret the data produced.

In summary, the definition of users and stakeholders was not driven by market considerations or generalized usability criteria, but by the nature of the problem addressed. Since the objective of the project is to render a previously unobserved variable measurable and to integrate it into performance analysis models, the primary user is the actor who uses the data to inform decisions, while the athlete remains the subject of measurement.

This conceptual distinction represents one of the foundational principles of the project and directly informs subsequent design choices related to system architecture and integration with the bicycle.

3.3 Why bottle cage?

Once the design question and the user profile were defined, the design process focused on identifying the most appropriate physical placement for the measurement system. This decision was addressed as a system-architecture problem, in which device placement directly affects data quality, measurement reliability, and compatibility with real-world cycling conditions. Since the objective of the project is to measure actual fluid intake during cycling activity without altering athlete behavior, system placement emerged as a primary design constraint rather than a secondary implementation detail.

The starting point of this analysis was the gesture of drinking in road cycling. Fluid intake on the bike is a rapid, standardized, and highly automated action, performed under dynamic and often high-intensity conditions. The athlete grabs the bottle, drinks, and replaces it within a few seconds, without the possibility—or necessity—of conscious attention. Any system requiring additional interaction, voluntary input, or explicit measurement procedures would inevitably alter this gesture and, as a consequence, distort the collected data. This principle constituted the first exclusion criterion for several alternative design scenarios.

A first scenario considered involved wearable systems, such as body-mounted sensors or athlete-integrated devices. While wearables offer proximity to the body and access to physiological signals, they are poorly suited for measuring fluid intake. The act of drinking does not generate a directly observable bodily signal without relying on complex inference or indirect physiological proxies. Moreover, introducing a wearable device dedicated to hydration measurement would increase cognitive load and potential discomfort, directly conflicting with the requirement of system transparency.

A second scenario explored was the integration of the system directly into the bottle. At first glance, this option appears functionally coherent, as the bottle is the object directly involved in fluid intake. However, further analysis revealed several critical issues. Bottles are consumable items, subject to frequent replacement, cleaning, and variability across models and suppliers. Embedding electronics and sensing components within the bottle would introduce significant constraints in terms of compatibility, maintenance, and reliability—particularly in professional contexts, where standardized and interchangeable bottles are an operational necessity. In addition, placing electronics in contact with consumable liquids raises concerns related to robustness, food safety, and product lifecycle management.

A further scenario involved positioning the system externally on the bicycle, for example on the frame, cockpit, or downtube. While such locations may offer more space for electronic integration, they remain indirect with respect to the drinking gesture. In these configurations, fluid intake would need to be inferred from secondary signals such as motion or state changes, reducing data reliability and increasing system complexity.

The comparative analysis of these scenarios led to the identification of the bottle cage cage interface as the most coherent solution with respect to the project requirements. The bottle cage is an element already integrated into the bicycle system, with standardized geometry and a well-defined function. It is directly involved in the drinking action, yet—unlike the bottle—it is structurally stable, fixed to the frame, and non-consumable. This placement allows the system to observe bottle removal and replacement without interfering with the liquid container itself and without introducing new constraints for the athlete.

An additional advantage of this placement concerns signal quality. Being rigidly connected to the frame, the bottle cage provides a stable mechanical reference, allowing load variations associated with bottle use to be interpreted in a more controlled manner compared to wearable or mobile solutions. This aspect is particularly relevant in road cycling, where vibrations, accelerations, and changes in bike attitude are continuous and unavoidable.

System placement was also evaluated in terms of operational scalability and adoption within professional teams. In WorldTour contexts, the introduction of new devices is constrained not only by performance considerations, but also by logistical, regulatory, and organizational factors. Solutions requiring dedicated management, frequent maintenance, or modifications to standard procedures tend to encounter resistance, regardless of their potential informational value. From this perspective, the bottle cage represents a favorable integration point, as it is already part of the standard bicycle setup and does not introduce a new category of equipment for technical staff to manage.

Positioning the system within a passive component already permitted by competition rules reduces uncertainty regarding race use. Compared to additional wearable devices or electronic systems integrated into critical frame components, the bottle cage (Figure 3) offers greater acceptability, particularly if the system does not significantly alter weight, aerodynamics, or the primary function of the component.

Finally, this placement supports a modular design progression. The bottle cage can serve as a first integration layer for the measurement system, keeping electronic complexity separate from both the bottle and the frame. This architecture allows future developments—such as integrated bottle–cage systems or multi-sensor configurations—without compromising compatibility with the base setup. In this sense, the bottle cage does not constrain future evolution, but rather provides a robust and flexible starting platform.

The bottle cage also offers practical advantages. Its mechanical accessibility, compatibility with 3D-printed components, and ease of mounting and removal make it particularly suitable for iterative experimentation. This characteristic was crucial during the early phases of the project, enabling exploratory prototypes focused on signal understanding and sensor calibration before moving toward more integrated solutions.

The choice to place the system at the bottle–bottle cage interface for my point of view is not opportunistic, but the result of an analytical process that evaluated and excluded multiple alternatives based on functional, behavioral, and systemic criteria. This placement respects the athlete's gesture, supports reliable measurement, and remains compatible with high-level cycling practice. From this point, the project can coherently progress toward system architecture definition and subsequent prototyping phases.

Figure 3: Standard road bike setup with 2 bottles - Colnago.com - 2025

3..4 Initial system architecture and data strategy

Once the system placement at the bottle–bottle cage interface had been defined, the project required the formulation of an initial system architecture. At this stage, architecture is intended not as a finalized technical solution, but as a conceptual structure capable of linking the physical act of drinking to a measurable and analyzable data output. The objective was therefore to define a framework robust enough to guide early technical decisions, while remaining flexible and open to iteration.
I search deeply in the market, and in this stage the system was conceived as composed of three interconnected layers:

- Signal acquisition, responsible for capturing the physical interaction associated with bottle use;

- Signal processing and logging, dedicated to transforming raw sensor output into interpretable data;

- Data export and analysis, aimed at enabling integration with existing performance analysis workflows.

This separation allowed the measurement problem to be addressed independently from data handling and visualization, avoiding premature constraints tied to specific technologies or platforms. In particular, the system was intentionally designed to produce a simple, readable and interoperable output, rather than real-time feedback or closed-loop user interaction.

Data strategy: measure first, connect later

In my initial formulation, the data strategy deliberately prioritized an offline, post-activity workflow. The system was conceived to generate exportable datasets—such as time-stamped CSV files—containing a chronological record of events related to bottle usage. This choice reflected a precise methodological stance: before attempting real-time transmission or ecosystem integration, it was necessary to verify whether a stable, interpretable signal could be obtained at all.

This decision was also aligned with the profile of the primary user. Performance engineers and coaches typically operate on exported datasets that can be reprocessed, synchronized and compared within analysis software. Open and simple formats are preferred, as they allow flexible manipulation and cross-correlation with existing performance metrics. In this sense, the CSV format was not intended as a final interface, but as a validation tool for the measurement concept itself.
Wireless communication strategies—such as Bluetooth or Wi-Fi—were considered as potential future extensions of the system, but intentionally postponed. Introducing real-time transmission at an early stage would have added layers of complexity that could obscure fundamental issues related to signal quality, noise, or calibration. By delaying connectivity, it became possible to isolate the sensing problem and reduce uncertainty during early experimentation.
This led to an incremental design approach, in which the first system architecture was intentionally minimal. The focus was placed on understanding sensor behavior, identifying relevant measurement ranges, and exploring signal stability under controlled and semi-controlled conditions. Integration with the broader digital ecosystem of cycling was therefore treated as a subsequent step, rather than a prerequisite. In practical terms, the guiding principle at this stage was: measure first, connect later.

Microcontroller as an experimental platform

Within this initial architecture, a programmable microcontroller was identified as the computational core of the system. Platforms from the ESP family were selected due to their balance between processing capability, low power consumption, ease of programming and potential for future wireless integration. At this stage, the microcontroller was not considered a definitive architectural choice, but rather an enabling tool for exploration.
The role of the microcontroller was to act as an interface between the physical interaction and the data layer: acquiring raw sensor signals, applying basic filtering logic, and logging data in a controlled manner. Early tests relied on serial logging through the development environment, allowing direct inspection of raw signals and facilitating calibration and debugging. In later iterations, Wi-Fi-based logging was introduced to decouple data acquisition from a physical cable, while maintaining a transparent and inspectable data pipeline.
The use of two different ESP platforms during experimentation—first an ESP32-WROOM module, followed by a more compact ESP32-C3 Mini—was part of this exploratory strategy. Rather than representing a linear upgrade, this transition allowed the evaluation of trade-offs between form factor, computational margin and integration complexity. While the WROOM module offered greater flexibility during early development, the C3 variant enabled experimentation closer to the spatial constraints of a bicycle-mounted system. These comparisons informed later considerations on miniaturization, without locking the project into a specific hardware solution at this stage.

Architectural implications

The adoption of a simple, modular architecture reflects an approach oriented toward uncertainty reduction. Road cycling represents a highly dynamic system, subject to continuous mechanical and environmental perturbations. In such a context, the ability to isolate and observe individual layers of the system is essential for building reliable measurements. Defining a minimal yet coherent architecture therefore represented a necessary step to support exploratory prototyping and

to ground subsequent design decisions in experimentally observed behavior rather than assumptions.
This initial system architecture does not aim to resolve all aspects of integration or usability. Instead, it establishes a controlled framework within which the sensing principle can be tested, evaluated and iteratively refined. The following chapter builds upon this foundation, describing how the conceptual architecture was translated into physical prototypes and how successive iterations progressively addressed signal reliability, integration constraints and system-level trade-offs.

3.5 Component analysis and sensing strategies for fluid intake measurement

Measuring real fluid intake during cycling activity requires a design approach that accounts for both the physiological and behavioral constraints discussed in Chapter 1, as well as the limitations imposed by a highly dynamic use context. Since intake cannot be observed as an autonomous physical quantity, the problem must be addressed through indirect measurement strategies, relying on proxy variables that are physically or functionally correlated with the act of drinking (Jeukendrup, 2014; Burke et al., 2011).

The objective of this section is to systematically analyze the main sensing principles and component families available, evaluating their suitability with respect to the requirements defined in the design brief.
Fluid intake during cycling occurs as a sequence of discrete events embedded within a continuous physical effort. From a design perspective, this requires translating an episodic action into a signal that can be meaningfully interpreted over time.
Two primary indirect measurement strategies were considered in this project:

(i) a mass-based approach, exploiting the relationship between fluid consumption and variation in system mass;

(ii) a force-based approach, based on measuring forces transmitted at the bottle–bottle cage interface during use (Webster & Eren, 2014).

The mass-based approach offers a direct and intuitive physical relationship between the measured quantity and the target variable. However, in a dynamic environment such as road cycling, mass variations are superimposed on inertial effects caused by accelerations, vibrations and changes in bicycle orientation. Conversely, the force-based approach allows greater mechanical integration flexibility, but introduces higher interpretative complexity, as the signal depends not only on the fluid quantity but also on user interaction and riding conditions.

For this reason, my selection between these strategies cannot rely solely on theoretical considerations, but must be informed by experimental behavior under realistic conditions (ISO 376; Webster & Eren, 2014).

Load cells as mass-based sensors

Load cells are widely adopted in industrial and scientific measurement systems due to their linearity, repeatability and well-established calibration procedures. Within the context of this project, they represent a reference solution for mass-based intake estimation, as they allow direct correlation between signal variation and bottle mass change (Webster & Eren, 2014).
From a design standpoint, load cells enable relatively straightforward calibration and offer sufficient resolution to detect small variations in fluid quantity, making them particularly suitable for validating the measurement principle. At the same time, their high sensitivity makes them susceptible to mechanical noise induced by road vibrations, surface irregularities and dynamic loading conditions (Figure 5). These effects can generate significant signal fluctuations that must be mitigated through careful mechanical integration and appropriate signal filtering strategies (Bishop, 2008; ISO 376).

Force Sensitive Resistors (FSR) and contact-based sensing

Force Sensitive Resistors are characterized by structural simplicity, minimal thickness and ease of integration. In a compact system such as a smart bottle cage, these characteristics are particularly appealing, as they support lightweight and low-profile designs (Interlink Electronics, FSR Integration Guide).
From a metrological perspective, however, FSRs present critical limitations. Their response is inherently non-linear, subject to drift and hysteresis, and strongly dependent on contact area and force distribution. As a consequence, achieving stable and repeatable calibration over time is challenging. In addition, the signal is highly sensitive to variations in user interaction and bottle positioning (Figure 4).
For these reasons, FSRs are poorly suited as primary sensors for quantitative intake measurement, but remain valuable as exploratory tools or auxiliary sensors for event detection and early system characterization (Baxter, 1997; Interlink Electronics).

Signal conditioning, amplification and data quality

The reliability of the acquired data is strongly influenced by the signal conditioning chain. Sensors such as load cells generate low-amplitude signals that require appropriate amplification and high-resolution analog-to-digital conversion before processing by a microcontroller (Texas Instruments, 2015; Analog Devices, 2018).
The choice of amplification and conversion architecture directly affects measurement sensitivity, noise susceptibility and overall stability. Dedicated signal conditioning solutions can significantly improve signal-to-noise ratio, but introduce trade-offs in terms of power consumption and electronic complexity. At this stage of the project, the focus was not on optimization, but on understanding these trade-offs and defining a signal acquisition chain robust enough to support repe-

atable experimental testing (Bishop, 2008).

Inertial Measurement Units (IMU) as contextual sensors

Inertial Measurement Units were considered as complementary sensors capable of providing contextual information about the dynamic state of the system. By measuring acceleration and rotation, IMUs can support the temporal identification of events such as bottle extraction and reinsertion, facilitating segmentation of the primary signal (Woodman, 2007).
It is important to note that IMUs do not provide direct information on fluid quantity. Their role is interpretative rather than quantitative, enabling discrimination between signal variations caused by user interaction and those generated by external disturbances. In this sense, IMUs enhance system robustness without replacing the primary sensing element (Woodman, 2007; Madgwick et al., 2011).

Power supply and energy constraints

Energy management constitutes an additional design constraint. In a bicycle-mounted system, battery selection directly impacts weight, volume and autonomy, and must be balanced against sensing, processing and logging requirements (Pletcher et al., 2009).
At this stage, the analysis focused on understanding the relationship between sampling frequency, session duration and total energy consumption. Rather than maximizing autonomy, the objective was to ensure reliable operation over the duration of a single training or testing session, with sufficient safety margins for experimental use (Texas Instruments, 2015).

Synthesis and implications for prototyping

The component and sensing analysis highlights that fluid intake measurement cannot be addressed through a single technological choice. Sensor selection, mechanical integration and signal processing are deeply interdependent, and no individual technology satisfies all project requirements when considered in isolation (Webster & Eren, 2014).
These considerations directly informed the configurations explored during the prototyping phase and clarified which compromises were acceptable given the project objectives. This section therefore establishes the technical and conceptual foundation for Chapter 3, where the strategies discussed here are translated into physical prototypes and evaluated through experimental validation.

3.6 Project brief

The objective of my project is the development of a system capable of measuring real fluid intake during high-performance cycling activity, without altering the athlete's habitual gesture and while producing a structured dataset compatible with existing performance analysis workflows.
The system is intended to operate in real-world conditions (training and, potentially, racing), to integrate with standard road cycling equipment, and to generate data that can be correlated with performance metrics such as power output and intensity distribution. The project is not oriented toward real-time feedback for the athlete, but toward the production of a reliable and interpretable dataset to support the decision-making processes of performance engineers, coaches and technical staff.

Functional requirements
Based on the project brief, the system must satisfy the following functional requirements:
FR1 – Measurement of real fluid intake
The system shall enable indirect measurement of the quantity of fluid ingested during activity through a physical proxy coherently related to the drinking gesture (Jeukendrup, 2014).
FR2 – Temporal resolution of intake events
The system shall produce a time-resolved dataset allowing identification of intake events and their distribution throughout the activity.
FR3 – Non-interference with athlete behavior
System operation shall not require additional actions, manual inputs or changes to the athlete's habitual drinking gesture.
FR4 – Compatibility with performance analysis workflows
The generated data shall be exportable and usable within standard performance analysis environments, both as aggregated values and as time series.

Technical requirements
The functional requirements translate into the following technical requirements:
TR1 – Integration within the bottle cage or bottle–cage interface
The system shall be integrated into an existing bicycle component, avoiding external or body-mounted devices.
TR2 – Sensor-based indirect measurement
Measurement shall rely on physical sensors capable of detecting force, mass or state variations associated with bottle usage (Webster & Eren, 2014).
TR3 – On-board data acquisition and logging
The system shall locally acquire and store data, ensuring continuity of measurement for the full duration of an activity.
TR4 – Expandability of system architecture
The architecture shall allow future extensions (e.g., wireless transmission or additional sensors) without requiring a complete redesign.

Constraints and boundary conditions
In addition to requirements, the project is bounded by a set of constraints defining the design space:
C1 – Mechanical and environmental robustness
The system shall operate under vibration, shocks, temperature variations and humidity typical of outdoor cycling conditions (ISO 4210; Bishop, 2008).
C2 – Weight and volume limitations
The integration shall not introduce mass or bulk that significantly affects bicycle performance or setup.
C3 – Energy autonomy
The system shall provide sufficient autonomy to cover at least a single training or racing session without intervention.
C4 – Use of standard consumables
Compatibility with standard cycling bottles shall be preserved, avoiding proprietary or dedicated consumables.

Product-oriented prototyping constraint

Beyond functional and technical constraints, my thesis project deliberately introduces an additional boundary condition related to product-oriented prototyping (mainly with my lab 3d printer). While early prototypes are primarily intended to validate the sensing principle, a later phase of the project explicitly targets the development of a prototype closer to a plausible real-world cycling product.
In this phase, the prototype is required to address performance-oriented design criteria typical of high-end cycling components, including aerodynamic integration, reduced overall volume, weight containment and increased attention to formal and aesthetic quality. The introduction of these criteria significantly reduces available space for sensors, electronics and power supply, and limits freedom in mechanical isolation and signal conditioning.

As a consequence, the project explicitly accepts a trade-off between measurement robustness and product realism. The final prototype is not designed to maximize measurement accuracy under all conditions, but to demonstrate how the sensing concept can be integrated within a form factor compatible with real cycling constraints. This choice reflects a Design Engineering approach in which prototyping serves not only technical validation, but also assessment of product feasibility and system integration.

Explicitly acknowledging this constraint is essential for the correct interpretation of experimental results presented in Chapter 3, and provides a transparent framework for understanding design decisions and compromises adopted throughout the project.

To assess system effectiveness during prototyping and testing, the following evaluation criteria are defined:
accuracy and repeatability of indirect intake measurement;

- signal stability under dynamic conditions;

- temporal coherence between drinking events and acquired signal;

- usability and transparency, understood as absence of perceived interference for the athlete;

- data usability, defined as the ability to export, synchronize and interpret intake data alongside performance metrics (Ulrich & Eppinger, 2016).

FRS sensor characteristics

- Thickness <1mm
- Force range 0.1-100N (depending on model)
- Response time <5 ms
- Non linear output
- Limited repeatibility
- Subjuct saturation at higher loads

Figure 4: Force Capacitive Sensor - 20 mm diameter

Load cell sensor characteristics

- Capacity from grams to hundreds of kgs
- Low linear error <0.03-01%
- High repeatibility
- Requires mechanical integration
- High accuracy
- Good long term stability

Figure 5: Load cell - 120 x 10 mm

4.0 Prototype 1: Measurement Principle Validation

4.1 Design concept overview

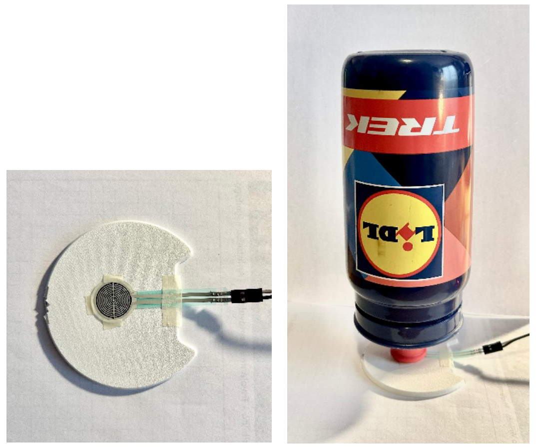
This section introduces the overall vision of the project and clarifies the role assigned to each prototype within the development process.

The principle of non-interference therefore constitutes a central design criterion and a key benchmark for evaluating the proposed solutions. The conceptual architecture of the system can be described as composed of three interrelated layers:

(i) a physical layer, in which the interaction between bottle and bottle cage generates a measurable variation;
(ii) an electronic layer, responsible for signal acquisition and data logging;
(iii) an informational layer, in which the data are structured to enable post-processing and correlation with performance parameters.
This separation allows the measurement problem to be addressed independently from data interpretation, while maintaining flexibility for future system evolution.

Given the high level of uncertainty and complexity inherent to the problem, the project adopts an iterative and progressive prototyping strategy. Two main prototypes were developed, each addressing a different design question.

The first prototype is conceived primarily as a measurement validation tool, developed in controlled and semi-static conditions. Its main objective is to verify the feasibility of extracting a coherent and interpretable signal from bottle usage, while minimizing external variables.



Figures 6 and 7: First Trial 1.1 for validate the sensor - Using FRS 20 mm diameter

The second prototype, by contrast, is oriented toward the exploration of the concept within a configuration closer to a real cycling product. In this phase, the project deliberately accepts a reduction in metrological performance in favor of constraints related to aerodynamic integration, volume reduction, weight containment and formal quality. This prototype is therefore not intended as an optimized measurement device, but as a product-oriented exploratory prototype, aimed at evaluating the feasibility of integrating the sensing concept within the real constraints of high-performance cycling equipment.

The coexistence of two distinct prototypes reflects a precise methodological choice: separating the validation of the sensing principle from the verification of its integration within a realistic product architecture. This distinction enables a correct interpretation of experimental results, avoiding mismatches between prototype objectives and evaluation criteria. At the same time, it supports a coherent design trajectory in which each prototype contributes specific insights into the overall problem.

The remainder of this chapter presents the two prototypes in detail, analyzing their mechanical and electronic configurations, testing methodologies and experimental outcomes. This analysis forms the basis for a critical discussion of system behavior and design trade-offs, preparing the ground for the conclusions and future developments discussed in Chapter 4.

4.2 Prototype 1 – Measurement principle validation

Before developing the integrated prototypes described in the following sections, the project included a preliminary experimental phase based on a static prototype. This prototype was conceived to validate the measurement principle under controlled conditions, isolating sensor behavior from the complexity of real-world cycling dynamics (Buchanan et al., 2007; Dyer, 2014).

The objective of this phase was not to replicate on-bike conditions, but to assess whether different sensing technologies could provide a signal that varied coherently and repeatably with changes in fluid quantity. The static prototype therefore acted as a simplified surrogate of the bottle–bottle cage interface, implemented through a dedicated test bench, a common approach in early-stage validation of sensing concepts (Ulrich & Eppinger, 2016).

I tried with this setup a direct comparison between two sensing strategies identified in Chapter 3: a contact-based solution using a Force Sensitive Resistor (FSR), and a mass-based solution using a load cell. The present section focuses on the first configuration and its experimental evaluation (Figures 6 and 7).

Preliminary static prototype with Force Sensitive Resistor (FSR)

This first configuration tried has a Force Sensitive Resistor as the primary sensing element. The FSR was initially selected due to its low cost, minimal thickness and ease of integration, characteristics frequently cited as advantages in compact and wearable sensing systems (Tekscan, 2020; Shull & Damian, 2015).
The sensor was integrated into a custom test bench fabricated via FDM 3D printing in PLA. The geometry was designed to apply controlled and repeatable vertical loads to the sensing surface, approximating the type of contact expected at the bottle–cage interface. During testing, the bottle was positioned upside down in order to localize the applied load and reduce variability associated with distributed mass along the bottle body, in line with standard practices for bench calibration of force-sensitive components (Dally, Riley, & McConnell, 1993).
To improve contact consistency and introduce a constant preload, a thin felt membrane was placed between the bottle and the sensor. This solution aimed to compensate for minor misalignments, reduce point-load effects and stabilize the initial response of the FSR, a technique commonly adopted to mitigate contact non-uniformities in pressure-sensitive materials (Hall & Holowenko, 1985).
From an electrical standpoint, the sensor was connected in a voltage divider configuration and read via the ADC of an ESP32 microcontroller, powered at 3.3 V. Two different reference resistances were tested in separate trials (100 kΩ and 10 kΩ) to explore the influence of circuit parameters on signal dynamics, as recommended in application notes and prior experimental studies on FSR conditioning (Tekscan, 2020).

Trial 1.1 – FSR with 100 kΩ reference resistor

In the first trial, I used a 100 kΩ reference resistor was used to maximize sensitivity in the lower force range. With no applied load, the sensor output stabilized around ~142 mV. As the bottle was progressively filled, the output voltage increased, reaching values close to 3015 mV at higher loads.
The test protocol involved incrementally increasing the bottle volume from 0 to 550 ml, assuming a density of 1 g/ml, with steps of approximately 50 g. Data were acquired via serial logging and exported for offline analysis, following established procedures for static calibration experiments (Dally et al., 1993).
While the sensor exhibited an initial response to increasing load, quantitative analysis revealed several critical limitations. The relationship between applied mass and output voltage was markedly non-linear, and repeatability across measurements was poor. More importantly, the sensor entered saturation at approximately 350–400 ml. Beyond this point, additional increases in volume produced negligible changes in output, rendering volumes between 400 ml and 550 ml effectively indistinguishable. In some cases, the signal exhibited non-monotonic behavior near saturation, further complicating interpretation.
These effects are consistent with the intrinsic behavior of FSRs, whose resistance change is governed by local pressure distribution rather than total applied force. Once the sensitive material enters a compressed regime, incremental load produces diminishing resistance variation, leading to signal saturation. The high value of the reference resistor, while beneficial at low loads, further compressed the usable dynamic range at higher forces (Tekscan, 2020; Shull & Damian, 2015).

Trial 1.2 – FSR with 10 kΩ reference resistor

To assess whether the observed saturation was primarily a consequence of the voltage divider configuration, under my professor advice I tried with a 10 kΩ reference resistor. All mechanical conditions were kept unchanged: identical test bench, inverted bottle configuration, felt preload and loading protocol.

This modification shifted the operating point of the circuit and reduced the extent of hard saturation observed in Trial 1.1. However, the resulting signal remained unsuitable for quantitative measurement. The output no longer followed a monotonic trend with increasing load: successive volume increments produced oscillating voltage values, including local inversions and regressions toward baseline.

In the final portion of the test (400–550 ml), the signal collapsed to values close to the unloaded condition (~150–160 mV), effectively eliminating any correlation between applied mass and output voltage. This behavior indicates that the dominant limitation was not electrical saturation, but the fundamental dependence of the FSR response on contact mechanics and pressure redistribution.

As load increased, micro-shifts in contact area, deformation of the felt interface and local stress redistribution across the sensing surface introduced variations larger than the signal contribution associated with mass change. Reducing the reference resistance altered sensitivity but did not restore physical coherence to the measurement, a limitation widely reported in the literature on FSR-based force estimation (Shull & Damian, 2015; Tekscan, 2020).

TRIAL 1.1 - ELITE FLY LIDL TREK			
ml_REAL	gr_REAL	mv_filt_RAW	mv_filt_FILTRED
0,00	0,00	142,00	142,00
EMPTY	34,00	142,00	142,00
50,00	84,00	142,00	142,00
100,00	134,00	2870,00	2870,00
150,00	184,00	3015,00	3015,00
200,00	234,00	2978,00	2978,00
250,00	284,00	2940,00	2940,00
300,00	334,00	3011,00	3011,00
350,00	384,00	2980,00	2980,00
400,00	434,00	3015,00 (MAX)	3015,00 (MAX)
450,00	484,00	3015,00 (MAX)	3015,00 (MAX)
500,00	534,00	3015,00 (MAX)	3015,00 (MAX)
550,00	584,00	2810,00	2810,00

Table 1: Data collection - Trial 1.1 - Inconsistency in the results.

Evaluation and implications

Across both trials, the FSR-based configuration failed to produce a signal that was monotonic, repeatable and information-rich over the target range of 0–550 ml. Even under carefully controlled static conditions, the sensor exhibited high variability and low robustness, preventing the definition of a reliable calibration function.

The signal was characterized by high entropy relative to the expected signal variation, making it unsuitable for distinguishing intake-related changes from noise (Cover & Thomas, 2006). In a dynamic cycling context, where additional disturbances such as vibration and acceleration are unavoidable, these limitations would be further amplified.

For these reasons, I excluded Force Sensitive Resistor as a primary sensing solution for subsequent development stages. Nevertheless, this experimental phase played a crucial role in refining evaluation criteria, highlighting the limitations of contact-based sensing in this application and motivating the transition toward a mass-based approach using a load cell.

4.3 Static prototype with load cell

Following the unsatisfactory results obtained with the Force Sensitive Resistor, the same conceptual test architecture was retained and applied to a second experimental configuration based on a rectangular load cell as the primary sensing element. This choice allowed the measurement principle to be isolated by keeping constant the acquisition logic, calibration procedure and test context, while modifying only the sensing technology.

Then I redesigned the current test bench (Figure 8) to accommodate the geometric and mechanical constraints of the load cell, with particular attention to load direction, support points and mechanical boundary conditions. Despite these adaptations, the overall system architecture remained conceptually equivalent to the previous configuration: the bottle acted as the applied load, the sensor measured the induced variation, and the signal was acquired and logged via microcontroller. This controlled setup enabled a direct comparison between sensing strategies while minimizing confounding variables.

All tests were conducted under static and controlled conditions, with the bottle positioned to apply the load along the sensitive axis of the load cell in a consistent and repeatable manner. The test protocol consisted of progressively increasing the liquid content of the bottle from 0 to 600 g. In line with standard experimental practice and reference data, an equivalence of 1 ml ≈ 1 g was assumed, considering water as the reference fluid (NIST, 2019).

Figure 8: Trial 1.3 experiment validation layout.

The calibration procedure followed the same methodology adopted in the previous phase. The output signal of the load cell, initially expressed in millivolts, was correlated with known mass increments applied in discrete steps. The acquired data were logged in tabular format and exported for offline analysis, enabling the construction of a calibration curve via linear regression. Based on this relationship, a conversion function was defined for subsequent implementation on the microcontroller, allowing raw sensor output to be mapped directly to mass values expressed in grams.

In contrast to the FSR-based configuration, the load-cell-based system produced clearly superior results. The sensor output exhibited a linear response over the entire tested mass range, with substantially reduced dispersion across repeated measurements. For identical applied loads, readings remained stable and consistent, indicating high repeatability. This behavior aligns with the intrinsic characteristics of strain-gauge-based load cells, which are specifically designed to provide reliable and reproducible measurements even at relatively low load levels (Omega Engineering, 2017).

Now I'm satisfied beacuse the signal quality is better, and itcan be attributed to several factors.
First, the load cell provides a direct measurement of force along a well-defined axis, significantly reducing sensitivity to load distribution and contact area effects. Second, the elastic response of the sensing element and its Wheatstone-bridge architecture ensure improved linearity and reduced susceptibility to local stress concentrations or minor misalignments when compared to contact-based resistive sensors (Dally, Riley, & McConnell, 1993). Finally, the use of dedicated signal amplification and high-resolution analog-to-digital conversion further enhances the signal-to-noise ratio, contributing to the overall stability of the measurement.

Overall, this experimental phase confirmed the validity of the mass-based sensing approach using a load cell as a robust solution for indirect fluid intake measurement. The results provided a solid foundation for advancing the project beyond principle validation, shifting the focus toward system integration and performance under more realistic and dynamic conditions. This transition defines the starting point for the subsequent prototyping iterations described in the following sections.
The electronic configuration of the first prototype was designed to support an experimental phase focused on validating the measurement principle. Priority was given to simplicity, reliability and ease of debugging, rather than to miniaturization or advanced system integration. At this stage, the electronics were conceived primarily as an instrument for observing the physical phenomenon, rather than as an optimized solution for final on-bike deployment.

Microcontroller platform: ESP32-WROOM
An ESP32-WROOM module was selected as the control and acquisition unit, due to its flexibility, available computational resources and ease of integration within rapid development environments. The ESP32 proved effective in managing sensor readings, performing preliminary signal processing and handling data logging, while preserving the possibility of future extensions toward wireless communication.
In this phase, the microcontroller was used mainly as an acquisition and debugging platform. Direct access to analog and digital pins, together with real-time monitoring through a serial connection, allowed close inspection of system behavior during testing and facilitated iterative calibration.

Signal amplification and conditioning
In the case of the load cell, the generated signal exhibits a very low amplitude and is not directly compatible with the analog input range of the microcontroller. For this reason, a dedicated load cell amplifier and analog-to-digital converter was employed, specifically the HX711 module, which is designed for high-resolution weighing applications.
The HX711 plays a central role in the acquisition chain, as it amplifies the signal from the load cell and converts it into a digital value with sufficient resolution to detect mass variations on the order of a few grams. The use of a dedicated conditioning component significantly improved the signal-to-noise ratio and provided a more stable output compared to solutions relying solely on the microcontroller's internal ADC.

Data logging via serial communication
During the static testing phase, acquired data were logged via serial communication, which served as the primary output channel. This choice enabled immediate access to raw data and greatly facilitated calibration procedures, verification of sensor behavior and preliminary signal analysis.
Serial logging allowed real-time observation of sensor readings during load application, making it possible to quickly identify anomalies or instabilities in the system. The transmitted data were subsequently stored and exported for offline analysis, forming the basis for calibration curve construction and for assessing measurement repeatability.

Sampling strategy
The sampling frequency adopted at this stage was defined in accordance with the static and controlled nature of the tests, as well as with the primary goal of validating the measurement principle. The system was configured with a sampling rate between 10 and 20 Hz, which was considered adequate for capturing slow, quasi-stationary load variations such as those associated with the gradual addition or removal of fluid from the bottle.
This choice was guided by two main considerations. First, the HX711 is designed for weighing applications and typically operates with output data rates in the range of 10–80 Hz, exhibiting improved signal stability at lower frequencies where electronic noise and high-frequency fluctuations are attenuated. Second, during static calibration and validation, higher sampling rates would not provide additional informative value, but would instead introduce increased signal variability and unnecessary complexity in data analysis.

Adopting a sampling frequency in the 10–20 Hz range therefore provided an effective compromise between temporal resolution, signal stability and processing simplicity. This configuration proved sufficient to accurately describe the observed load variations during testing and also served as a useful reference for subsequent project phases, in which sampling frequency may be reconsidered in light of dynamic conditions and more stringent requirements associated with real-world cycling use.
Overall, the electronic configuration and acquisition strategy adopted for the first prototype enabled the collection of a coherent and interpretable dataset, providing a solid foundation for validating the measurement principle and for progressing toward more integrated, product-oriented prototypes.

TRIAL 1.3 - ELITE FLY EF EASYPOST		
gr_REAL	gr_REAL	mv_filt_RAW
0,00	0,00	-0,728760
EMPTY (54 gr)	50,00	-0,794880
50,00	100,00	-0,862280
100,00	150,00	-0,927750
150,00	200,00	-0,994180
200,00	250,00	-1,058030
250,00	300,00	-1,127350
300,00	350,00	-1,195310
350,00	400,00	-1,260600
400,00	450,00	-1,330650
450,00	500,00	-1,393460
500,00	550,00	x
550,00	600,00	x

Table 2: Data collection - Trial 1.3 - First load cell validation.

4.4 Calibration summary and lessons learned

The calibration and experimental phase was very importat for me, and the static prototype provided clear and quantitative evidence regarding the suitability of the investigated measurement principles. By directly comparing a Force Sensitive Resistor (FSR) and a load cell while keeping the test logic, calibration procedure and acquisition chain unchanged, it was possible to isolate sensor behavior and evaluate each solution objectively.

FSR-based calibration outcomes

Calibration tests performed with the FSR revealed a non-linear and poorly repeatable relationship between applied load and output signal. Under identical loading conditions, successive measurements exhibited significant variability, with deviations comparable in magnitude to the variations of interest for the project. Even after applying filtering strategies and calibration models, the observed error remained high and strongly dependent on contact conditions and mechanical configuration.
This behavior is consistent with the known characteristics of Force Sensitive Resistors, whose response depends on localized pressure distribution rather than on total applied force, resulting in pronounced non-linearity, hysteresis and sensitivity to contact mechanics (Interlink Electronics, 2016; Dargie & Poellabauer, 2010). As a result, the FSR proved unsuitable for reliable quantitative estimation of fluid intake, particularly in view of the dynamic operating conditions expected in cycling applications.

Load cell calibration and performance

I tried an alternative configuration employed a rectangular load cell with a nominal capacity of 5 kg and approximate dimensions of 120 × 24 × 24 mm, integrated into a test bench adapted to the mechanical constraints of the sensor. Test conditions were kept consistent with previous trials to ensure a meaningful comparison. The bottle acted as the applied load, while the signal was acquired via an ESP32 microcontroller interfaced with an HX711 load cell amplifier, selected for its widespread use in precision weighing applications and high-resolution bridge readout capability (Avia Semiconductor, 2019).
Calibration was performed by applying known loads in the range 0–500 g, assuming the equivalence 1 ml ≈ 1 g. This approximation is commonly adopted in experimental contexts when water is used as reference fluid, due to its near-unit density at ambient temperature (Çengel & Boles, 2015). This interval was chosen to cover the operational range of a standard cycling bottle while avoiding extrapolation beyond calibrated values.
Experimental results showed a strongly linear and monotonic relationship between applied mass and electrical signal, with minimal dispersion across repeated measurements. The resulting linear calibration model can be expressed as:

$$\text{grams} = -546.25 - 750.32 \cdot \text{mV}$$

The coefficient of determination was $R^2 = 0.99995$, indicating an almost perfect correlation between input and output. The root mean square error (RMSE) was approximately 1.07 g, demonstrating high precision under static conditions. Such performance is consistent with the expected behavior of strain-gauge-based load cells when combined with dedicated amplification and high-resolution analog-to-digital conversion (Fraden, 2016).

No saturation effects or significant non-linearities were observed within the calibrated range. Unlike the FSR-based trials, constant mass increments produced proportional and coherent signal variations, with no inversions or collapse of usable signal range. Signal stability over time was also high, with limited dispersion under repeated identical loads, confirming good repeatability.
The negative slope of the calibration curve is attributable to the inversion of the A+ and A− terminals of the strain gauge bridge. While this does not affect measurement quality, it was intentionally preserved and documented to maintain transparency regarding the acquisition architecture, in line with standard instrumentation practices (Doebelin & Manik, 2011).

Design implications
The achieved accuracy (≈ ±1 g) is more than adequate for the intended use case. For a 500–600 ml bottle, this corresponds to an error well below 0.2%, supporting not only estimation of total fluid intake but also time-resolved analysis of mass variation during activity.

At a design level, this phase clarified the trade-off between measurement reliability and integration complexity. Compared to an FSR, the load cell is inherently bulkier, stiffer and heavier, introducing constraints in terms of packaging and mechanical integration. However, experimental evidence clearly shows that this compromise is justified: the stability, linearity and interpretability of the load cell signal far outweigh the drawbacks associated with increased volume.

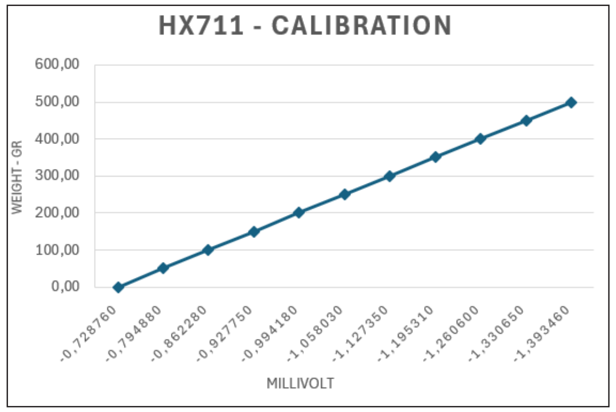


Table 3: Trial 1.3 with load cell - $R^2 = 0.99995$ → almost perfect (linear) fit

Lessons learned and outlook

The load cell demonstrated a stable and linear response across the full tested range (0–600 g), with low dispersion and high repeatability. The ability to derive a robust calibration curve enabled straightforward implementation of a scaling function directly on the microcontroller, yielding measurements expressed in grams from raw sensor data—an essential requirement for practical use and downstream analysis.
While the volumetric footprint of the load cell is approximately an order of magnitude larger than that of an FSR, this increase reflects the mechanical architecture required to achieve elastic deformation and measurement stability. The additional volume therefore represents the physical cost of reliable data acquisition rather than an inefficiency of the solution.
Within the scope of measurement principle validation, this trade-off is acceptable and justified. Moreover, the quantified volume and mass of the sensor provide a concrete baseline for subsequent design iterations, particularly those targeting a more compact, aerodynamically integrated "road-ready" prototype.

What surprise me in this stage is the direct connection between the static and dynamic prototype, so now this direction becomes central in the following prototyping phases, where aerodynamic integration and system compactness gain increasing relevance.

4.5 Experimental validation in quasi-real conditions

Experimental setup and testing context
Building on the positive results obtained in Trial 1.3 and using the same calibration parameters, a more advanced experimental test bench was developed to approximate the geometric and structural conditions of real on-bike use. At this stage, the objective was no longer limited to validating the measurement principle under ideal conditions, but extended to assessing its robustness when subject to realistic mounting constraints, such as frame orientation, bottle cage inclination and non-vertical load distribution.

The test bench was constructed using my old Cannondale MTB frame, selected as a rigid and structurally representative support of a real bicycle chassis. The prototype was mounted in correspondence with the down tube / top tube area, with an inclination of approximately 20° relative to the horizontal plane, consistent with the geometry observed on many contemporary road and gravel bicycles. The sensing system—comprising a 1 kg load cell, an HX711 amplifier and a microcontroller—was fixed to the frame using custom 3D-printed mounting plates, designed to replicate as closely as possible the mechanical constraints anticipated in the final product configuration.
Compared to the previous static test setups, this configuration introduces a significant increase in complexity. The gravitational force no longer acts along an axis perfectly aligned with the primary sensitivity direction of the load cell, and the applied load is partially resolved into components along inclined planes. From a measurement perspective, this represents a critical condition, as it directly tests whether the system can maintain a coherent and interpretable response in the presence of non-ideal loading components, which are unavoidable during real-world cycling use (Doebelin & Manik, 2011).

Experimental results and calibration validity

The test was carried out by applying progressive mass increments to the bottle, following the same procedure adopted in previous trials, while keeping the calibration model derived from Trial 1.3 unchanged. No additional calibration was performed specifically for the inclined configuration, as the purpose of this phase was to evaluate the transferability and robustness of the existing calibration model under different geometric conditions.

The acquired data show a regular, monotonic and coherent system response across the entire tested range, up to approximately 500 g, confirming the validity of the mass-based approach. The applied calibration model remains linear, with parameters consistent with those previously obtained and a coefficient of determination of $R^2 \approx 0.99997$, indicating an excellent correlation between measured signal and applied mass even under non-ideal loading conditions.

The estimated root mean square error (RMSE) is approximately 0.86 g, slightly lower than the value observed in the purely static bench tests. This result suggests that the inclination of the system and the altered force distribution do not introduce significant distortions in the measurement, at least within the static and quasi-static regime analyzed. Such behavior is coherent with the operating principles of strain-gauge-based load cells, which are designed to provide stable and linear outputs even when subjected to off-axis loading components, provided that these remain within the elastic working range of the sensor (Fraden, 2016).

Also here I am surpiresed because I saw relevant a stability in the measurement when accounting for the mass of the empty bottle itself (approximately 79 g), which is correctly detected and compensated in the computation of usable fluid volume. This indicates that the system can reliably distinguish mass variations due to fluid intake even when the total load includes structural components in addition to the liquid. From an application standpoint, this behavior is essential, as it allows the bottle to be treated as a non-ideal, composite system rather than as a simplified container with negligible tare mass.

Figure9: Test Bench with MTB frame, first measurment in a semi-real condition

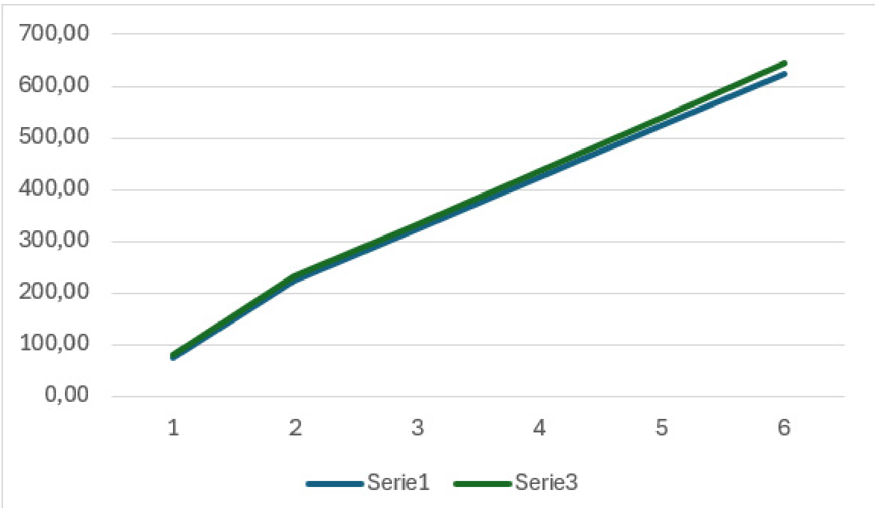


Table 4: A gradual drift is observed in the measurements, error increasing progressively

TRIAL 2.1			
gr_REAL	gr_PLOTTED	ml_PLOTTED	PASS/FAIL
74,00	79,80	1,00	
224,00	232,70	154,00	
324,00	334,10	255,00	
424,00	435,20	356,00	
524,00	539,00	460,00	
624,00	644,20	565,00	

Table 5: The sensor reach a maximum deviation of +15 grams in the final reading

Discussion and design reflections

This test represents a pivotal step in the development of the system. For the first time, a measurement principle validated under laboratory conditions was evaluated within a structurally realistic configuration, in which sensor orientation, support stiffness and frame geometry directly influence how the load is transmitted to the load cell. The fact that the system maintains a high level of accuracy under these conditions provides strong evidence of the robustness of the design choices made in the earlier phases of the project.

At a more personal level, this test (Figure 9) marked a shift in how the project itself was perceived. In the early stages, the load cell appeared as an excessively bulky solution, seemingly at odds with the constraints of high-performance cycling components. The results obtained in the frame-mounted configuration, however, show that data reliability can justify substantial compromises in terms of integration and packaging. In other words, the test conducted on a real bicycle frame reframed the design problem: the critical question is no longer whether the system works, but how it can be integrated in an intelligent and coherent way within the constraints of a performance-oriented product.

This experimental setup therefore acts as a conceptual bridge between the static prototype and the more integrated “road aero” prototype developed in the subsequent phases. While the results do not yet constitute a full validation under dynamic riding conditions, they provide solid evidence of the robustness of the measurement principle, opening the way toward further developments focused on miniaturization, formal integration and testing in real-world use scenarios.
The maintenance of high accuracy despite an inclination of approximately 20° relative to the horizontal further confirms the suitability of the mass-based approach for this application context. The measurement remains stable even when the load is not applied along the ideal sensing axis, reinforcing confidence in the underlying sensing strategy and its applicability to real bicycle geometries.

During this experimental phase, the data acquisition and processing code was also extended to include an initial logic for identifying the type of bottle in use. Specifically, the empty weights of two widely adopted professional cycling bottles—Elite Fly and Tacx Shiva—were incorporated into the model. The intention was to explore whether the system could automatically recognize the bottle model based on the initial detected mass, without requiring any manual input from the athlete or technical staff.

The tests indicate that this functionality is not yet sufficiently reliable. Variability introduced by manufacturing tolerances, residual liquid, bottle wear and mounting conditions leads to a dispersion in empty bottle mass that makes robust classification based solely on this parameter impractical. As a result, automatic bottle recognition was considered

immature and was not retained as an active feature of the system in this phase of the project.
Nevertheless, the inclusion of this logic played an important exploratory role. It highlights the potential for the system to evolve from a pure measurement device into a more adaptive platform, capable of adjusting calibration parameters and data interpretation based on contextual information. From a design standpoint, this helped clarify that the value of the project does not reside exclusively in the sensor or electronics, but in the possibility of building a system that can progressively learn and adapt.

The integration of additional sensing modalities, more advanced signal analysis or classification approaches could make this feature viable in later iterations. The margin for improvement identified through these tests further reinforces the design relevance of the system and contributes to outlining a coherent development roadmap for the next phases of the project.

4.6 Dynamic measurement test and signal filtering

Building on the positive results obtained in the static and quasi-real tests described in the previous sections, an additional experiment was conducted to evaluate the system behavior under conditions closer to real-world use.
This phase introduced a first signal filtering logic specifically oriented toward dynamic measurement, shifting the focus from validation of the measurement principle to the system's ability to provide coherent readings in the presence of small load fluctuations.

These micro-variations are characteristic of the real interaction between bottle, bottle cage and bicycle frame during cycling activity and represent a critical challenge for any mass-based sensing approach.
To address this, the acquisition code was updated to:

- incorporate the sensor calibration derived from the previous trials;

- introduce a measurement filter that becomes active when the sensor detects a variation greater than a predefined threshold (40 g), interpreted as a bottle usage event (placement or removal);

- generate a direct estimate of fluid volume as a function of the filtered weight signal, expressed in milliliters.

The rationale behind this strategy was to reduce signal noise and isolate meaningful variations, preventing minor oscillations or mechanical disturbances from propagating into the final intake estimation.

Experimental results analysis

The results of Trial 2.1 show an initially coherent system behavior, followed by a progressive degradation in measurement accuracy as the load increases. For low load values, corresponding to the first measurements, the difference between the real weight (gr_REAL) and the estimated weight (gr_PLOTTED) remains limited. For instance, at a real value of 74 g, the system returns an estimate of approximately 79.8 g, resulting in a small and acceptable error within the intended application context.

As the load increases, however, the error grows progressively. At intermediate values (approximately 224–324 g), the estimated weight shows an overestimation on the order of 8–10 g. In the final measurements, close to full bottle load (524–624 g), the error reaches values of approximately 15–20 g. This trend is clearly visible in the associated plot, where the estimated measurement curve gradually diverges from the ideal reference.

When translated into volume estimation, this growing error results in an increasing discrepancy between the real fluid volume and the calculated one, ultimately leading to a negative evaluation of the test outcome. Although the overall response remains broadly linear, the cumulative error makes the system unreliable for precise intake measurement under dynamic conditions.
This result highlights a key limitation of the current filtering strategy: while effective at suppressing high-frequency noise, it introduces a systematic drift that accumulates over larger load ranges, compromising accuracy in conditions representative of real use.

Discussion and conclusions

The analysis of this test highlights how the introduction of filtering strategies and threshold-based logic, while improving initial signal stability, can introduce non-negligible side effects in a cumulative measurement system such as fluid intake monitoring. In particular, the filter based on a fixed variation threshold (>40 g) favors the detection of discrete events, but fails to adequately handle the continuous micro-variations that characterize real bottle usage. As a result, measurement inaccuracies progressively accumulate over time, becoming increasingly evident at higher fluid volumes.

This outcome represents another critical turning point. While the load-cell-based measurement principle proves valid and reliable under static and quasi-static conditions, the results clearly show that directly transferring static measurement models to dynamic scenarios is not straightforward. System dynamics introduce phenomena—such as vibrations, small relative movements, friction effects and unintentional load variations—that cannot be effectively addressed through simple filtering techniques or fixed thresholds alone.

This test clarified that the core complexity of the problem no longer lies in the sensing hardware or in the electronic architecture, but in the interpretation logic applied to the data. The challenge is not measuring weight per se, but distinguishing, over time, which signal variations are genuinely associated with fluid intake and which are artifacts generated by the usage context.
From this view, the negative outcome of Trial 2.1 should not be interpreted as a failure, but rather as confirmation of the need for more sophisticated approaches, potentially involving advanced temporal analysis, adaptive models or the integration of additional sensing modalities.
This test therefore concludes a fundamental exploratory phase of the project. It explicitly defines the limits of the current approach and provides a clear foundation for future development directions, which will be discussed in the final chapter.

Dynamic measurement test and signal filtering

In Trial 2.1, the data acquisition code was further developed to address the problem of measurement under dynamic conditions, introducing an initial temporal filtering strategy aimed at stabilizing the signal. The algorithm was designed to identify significant load variations, interpreted as bottle usage events (placement or removal), and to distinguish them from continuous micro-variations caused by vibrations, mechanical settling or system noise.
To this end, a variation threshold of approximately 40 g was introduced. Weight changes below this threshold were not classified as relevant events. While this choice effectively reduces noise and improves the stability of early readings, it also introduces a relevant side effect: the sensor progressively becomes less sensitive to small weight variations occurring over short time intervals. In practice, variations smaller than 40 g distributed over relatively brief periods (on the order of 10–20 seconds) tend to be filtered out or attenuated, reducing the system's ability to capture gradual but real changes in bottle content.
In parallel, to further improve signal stability and limit the amount of generated data, the effective sampling strategy was defined as the average of multiple readings acquired over a temporal window of approximately 15 seconds. This form of temporal averaging was introduced with a dual purpose. On the one hand, it provided a more stable estimate of the measured weight; on the other, it reduced data density, simplifying plotting and easing signal inspection during the debugging phase. At this stage, all readings were visualized and analyzed exclusively through the Arduino IDE serial log, without the use of external visualization tools or dedicated dashboards.

Effects of filtering on experimental results

The analysis of the Trial 2.1 data shows that the combined introduction of a fixed threshold (40 g) and temporal aggregation of readings (≈15 s) produces an initially stable behavior, but not without critical limitations. In the early stages of the test, when weight variations are more pronounced, the system returns coherent values that remain relatively close to the real ones. As the load increases and variations become more gradual, however, the error tends to accumulate progressively.
This behavior can be attributed to the fact that the filter, while improving signal stability, attenuates slow and low-amplitude variations, which are instead characteristic of real bottle usage, especially during progressive emptying. As a consequence, the system tends to "lag" in updating the measurement, leading to an overestimation of the remaining weight and to a growing error in volume estimation.
When moving from static measurement to conditions closer to real on-bike use, it becomes essential to define a balance between sampling frequency, averaging window and event detection thresholds. During cycling, the system does not observe a "clean" signal associated solely with bottle weight, but rather a signal superimposed with multiple dynamic disturbances: vibrations transmitted through the frame from the road surface, micro-impacts, oscillations of the bottle cage, structural flexions, and load variations related to rider posture and pedaling. In other words, the static weight of the bottle is continuously modulated by dynamic components that, if not properly managed, risk being interpreted as real changes in liquid content.
From a signal processing perspective, this situation reflects the classic trade-off between sensitivity and stability. Sampling too frequently and reporting raw readings would make the system highly reactive, but also extremely vulnerable to noise: high-frequency fluctuations typical of road-induced vibrations would be translated into false weight changes. Conversely, sampling at a lower rate or applying averaging over excessively long temporal windows produces a more stable signal, but increases system latency and reduces the ability to capture real variations occurring over short time intervals.

At this stage, the adoption of an averaging window on the order of approximately 15 seconds was motivated by two main reasons. The first is experimental: temporal averaging attenuates rapid oscillations and helps decouple the quasi-static signal (actual weight) from dynamic components. The second is operational: reducing the number of plotted and observed points in the Arduino IDE log simplifies debugging and makes trends more readable, preventing noise from masking differences between conditions. This choice therefore represents a deliberately conservative compromise, oriented toward stability and readability rather than maximum temporal resolution.

In parallel, the introduction of a threshold of approximately 40 g was a pragmatic decision related to the intended use context. In real cycling conditions, variations on the order of a few tens of grams can easily be generated by vibrations or micro-movements of the system (for example, a sharp impact on a pothole or the natural oscillation of the bottle inside the cage). Setting a threshold therefore reduces false positives, i.e. the risk of interpreting noise as a meaningful event.

At the same time, this choice introduces a clear limitation: the system becomes less sensitive to small but real variations in liquid content, especially when distributed over short intervals (e.g. repeated small sips) or when the athlete drinks in a highly fragmented manner. In other words, the threshold protects against noise, but can effectively "cut away" real information.

This phase made explicit a fundamental aspect of the project: intake measurement is not only a sensing problem, but a problem of temporal signal interpretation. The numerical values adopted (≈15 s averaging window and ≈40 g threshold) do not represent optimal parameters in an absolute sense, but rather reasoned initial hypotheses reflecting a balance between:

(i) the need to stabilize a signal disturbed by the dynamic cycling environment,
(ii) the need to preserve sufficient sensitivity to detect real changes in bottle content,
(iii) the need to keep the system observable and debuggable during the prototyping phase (IDE-based logging).

This trade-off clarifies why the evolution toward a truly usable system does not rely solely on hardware improvements, but requires a substantial tuning phase and, potentially, the development of more advanced algorithms (such as adaptive filters, event detection based on temporal patterns, or sensor fusion). This awareness guided the subsequent optimization of parameters and provided a methodological foundation for advancing to the next phase of the project.

Parameter adjustment and transition to the next phase

Following these results, the filtering and acquisition parameters underwent an initial phase of empirical tuning, aimed at identifying a more balanced compromise between system stability and sensitivity. In particular, minor adjustments were introduced to temporal parameters and variation thresholds, reducing the "insensitivity" of the system to small weight changes and improving its ability to track progressive load variations over time.

Without yet introducing advanced filtering strategies, these adjustments allowed the system to achieve a more stable balance between noise suppression and signal responsiveness, sufficient to move forward to the subsequent phases of the project. It is important to emphasize that the objective of this stage was not to reach a definitive solution for dynamic measurement, but rather to verify whether, through appropriate calibration and a conscious management of acquisition parameters, the system could become usable as a foundation for further development.

This step clarified that the real main difficulty no longer lies in measuring weight itself, but in the temporal interpretation of the data. Fluid intake measurement is not a purely static problem, but a dynamic and cumulative one, in which the choice of sampling rate, filtering strategy and detection thresholds directly affects the quality of the extracted information. The outcome of Trial 2.1, while highlighting clear limitations, provided valuable insights that enabled a more informed transition toward the next phase of prototype development.

4.7 Prototype 2 – First fully integrated system

This sub-chapter describes the development and validation of the first fully integrated and operational prototype of the fluid intake monitoring system, installed directly on a real bicycle and tested under conditions close to its intended final use. Unlike the previous phases, which primarily focused on validating the measurement principle and analyzing the behavior of individual components under controlled conditions, the work presented here addresses the system as a whole, in which sensor, hardware architecture, embedded code and mechanical integration interact simultaneously.

The prototype described in this section represents a turning point in the project. It is no longer a test bench or a conceptual demonstrator, but a design artifact capable of producing coherent data once mounted on a complete bicycle. At this stage, the project clearly enters a product-oriented dimension, where technical choices must confront real-world constraints such as frame geometry, vibrations, road surface irregularities and variability in usage conditions.

My objective of this chapter is not to demonstrate a flawless system, but to transparently document what works, what works only partially, and what remains unresolved. In this sense, the prototype is analyzed as a first operational system, capable of validating the feasibility of the proposed approach while simultaneously revealing the limitations that will guide future developments.

The following subsections progressively describe the sensor design and mechanical integration, the hardware and embedded system architecture, the adopted calibration model, the experimental results obtained on a real bicycle, and the main design considerations that emerged from this phase.

Sensor and mechanical design

The second prototype was conceived as a single structural component capable of integrating the sensor, electronics and interface with the bicycle frame into one coherent geometry. From a formal standpoint, the prototype adopts a "T-shaped" configuration, in which the different parts of the object are clearly differentiated according to their function.

The rear section of the prototype, characterized by a larger volume, houses the entire electronic architecture of the system. This area accommodates the ESP32-WROOM microcontroller, the HX711 load cell amplifier, the MPU6050 accelerometer (IMU), the load cell itself, and the necessary wiring for connecting the various components. This section is designed to be mounted directly onto the bicycle frame using standard M5 threaded inserts, with conventional spacing, which are present on the vast majority of modern frames. This choice allows the system to be installed without requiring custom adapters or structural modifications to the bicycle.
The front section of the prototype is instead tapered and functionally dedicated to measurement. This is where the load cell is positioned, acting as the core sensing element of the system. The thinner, elongated geometry was designed to channel the load transmitted by the bottle cage toward the sensor, minimizing dispersion and misalignment. This portion of the prototype includes the M5 mounting holes required to attach a standard bottle cage, ensuring compatibility with bottle cages and bottles commonly used in road and gravel cycling.
The entire prototype was manufactured using 3D printing in PETG, a material selected for its favorable balance between mechanical strength, toughness and dimensional stability. Compared to stiffer but more brittle materials, PETG allows partial absorption of vibrations and micro-impacts—an advantageous property in a cycling context—while still maintaining the local stiffness required for effective load transmission to the load cell.
The form of the prototype was driven primarily by function rather than by aesthetic considerations. The geometry was developed following a "shrink-wrapped" logic around the components: the overall volume closely follows the actual footprint of the electronic and mechanical elements, avoiding unnecessary bulk and minimizing non-functional space. This approach made it possible to keep the prototype relatively compact, despite accommodating components that are inherently bulky, such as the load cell and the microcontroller.

Overall, the sensor design reflects an advanced prototyping stage, in which the priority is to demonstrate the feasibility of integration and compatibility with existing cycling standards. The use of conventional mechanical interfaces—such as M5 fasteners and standard frame spacing—positions the system within an already consolidated ecosystem, reducing barriers to adoption and laying the groundwork for future developments focused on formal refinement, aerodynamic optimization and manufacturability.

Hardware architecture and embedded system

Now it's important to clarify that the development of the hardware and embedded architecture presented in this chapter does not stem from a specialized background in electronics, which is not the core focus of the author's academic training. The competencies required to design and implement the system were progressively acquired during the thesis work through self-directed study, hands-on experimentation and iterative prototyping. Within this framework, electronics is not treated as an end in itself, but as a design tool supporting product development and validation. The results presented here should therefore be understood as the outcome of a learning-by-doing process embedded in the design activity.
The hardware architecture of the second prototype was conceived to balance measurement reliability, system simplicity and openness to future development. At this stage, the goal was not extreme miniaturization, but the creation of a stable and modular platform capable of supporting further iterations at both hardware and software level.
At the core of the system is an ESP32-WROOM microcontroller, selected for its combination of computational capability, integrated connectivity and widespread adoption in advanced prototyping contexts. The ESP32 manages sensor data acquisition, applies calibration models, handles basic filtering logic and logs the measured values. Although Wi-Fi and Bluetooth connectivity are not fully exploited in this prototype, their availability was considered a strategic asset for future evolution toward real-time data transmission and system integration.
Weight measurement is performed through a load cell interfaced with an HX711 load cell amplifier, which acts as the analog-to-digital front-end for reading the strain gauge bridge. The HX711 was chosen for its high resolution, measurement stability and compatibility with low-power microcontrollers. The digitized signal is transmitted to the ESP32 for further processing and filtering. This separation between analog measurement and digital processing contributes to a cleaner measurement chain and facilitates future modifications or refinements.
An inertial measurement unit (IMU) was also integrated into the system, with the purpose of exploring, in later stages, the possibility of compensating for variations in bicycle orientation and inclination. In the current version of the prototype, IMU data are not actively used in the calculation of weight or fluid volume. Nevertheless, its inclusion reflects a design choice oriented toward scalability and the potential implementation of sensor fusion strategies in future iterations.

Regarding power supply, the system was designed to operate using an external energy source, consistent with an experimental phase in which system stability and observability were prioritized over autonomy. This choice simplified development and debugging, reduced the number of interacting variables and allowed more direct control over electronic behavior during testing.

The internal layout of the components follows a functional logic. The microcontroller and the HX711 amplifier are located in the rear section of the prototype, close to the frame mounting interface, while the load cell is physically separated and positioned in the front section dedicated to sensing. This arrangement reduces mechanical interference, simplifies cable routing and preserves a compact overall volume (image 10). Overall, the hardware architecture of the prototype represents a deliberate compromise between complexity and robustness. It enables validation of system behavior under realistic conditions while maintaining a high degree of control over individual components—an essential aspect for a project positioned at the intersection of technical experimentation and product-oriented design.

Firmware and data processing logic

The firmware development of the second prototype builds directly on the experience gained during the previous phases, particularly on the last static prototype validated on the test bench. The overall software architecture—including load cell signal acquisition, application of the calibration model, basic filtering and TARE—was initially preserved to ensure continuity and comparability of results across experimental phases.
During the early testing sessions with the prototype mounted on a complete bicycle, data logging was performed through a wired serial connection, with real-time visualization of sensor values via the Arduino IDE, following the same approach adopted in earlier trials. This solution, however, quickly revealed several limitations. The presence of the USB cable connected to the microcontroller introduced both mechanical and electrical interference, affecting the behavior of the system. From a mechanical standpoint, the cable acted as a physical constraint, slightly altering force distribution and limiting the free movement of the prototype, thereby reducing the representativeness of the measurement with respect to real use conditions. From an electrical perspective, the direct connection to a computer introduced potential noise sources and further constrained the possibility of testing the system in more dynamic configurations (Monk, 2004; Lyons, 2011).

To overcome these limitations, the firmware was adapted to support wireless data acquisition by leveraging the integrated Wi-Fi capabilities of the ESP32-WROOM microcontroller. In this configuration, the microcontroller operates as a local server, transmitting measurement data over a Wi-Fi network and making them accessible through a dedicated web page. The data can be visualized in real time on any device connected to the same network, such as a laptop, tablet or smartphone. This approach completely removes the physical cable connection, significantly reducing external interference and improving the ecological validity of the tests.

From a design perspective, the transition to Wi-Fi-based logging represents a meaningful step forward. The physical separation between the measurement system and the visualization device allows the sensor behavior to be observed in a more neutral condition, without external constraints influencing the signal. Moreover, web-based visualization provides a more intuitive and continuous overview of signal evolution over time, facilitating the identification of anomalies, drift phenomena or instability during experimental sessions (Fielding & Taylor, 2016; Banzi & Shiloh, 2022).

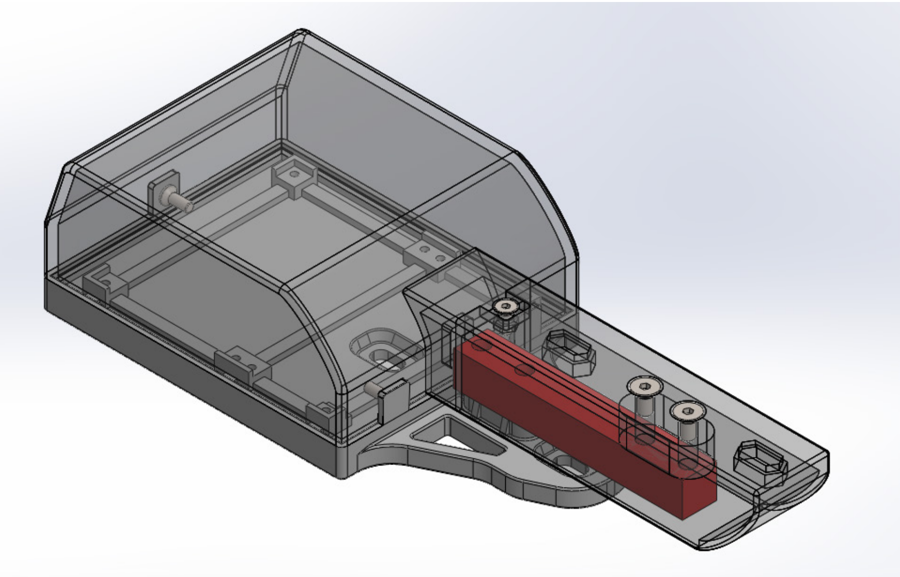
It is important to note that, at this stage, Wi-Fi communication is not used for structured or persistent data transmission (e.g., database storage or integration with external platforms), but exclusively as a tool for experimental observation and validation. Nevertheless, this architectural choice naturally anticipates future developments, in which wireless connectivity could enable real-time data streaming, synchronization with performance analysis platforms or integration within broader digital ecosystems.

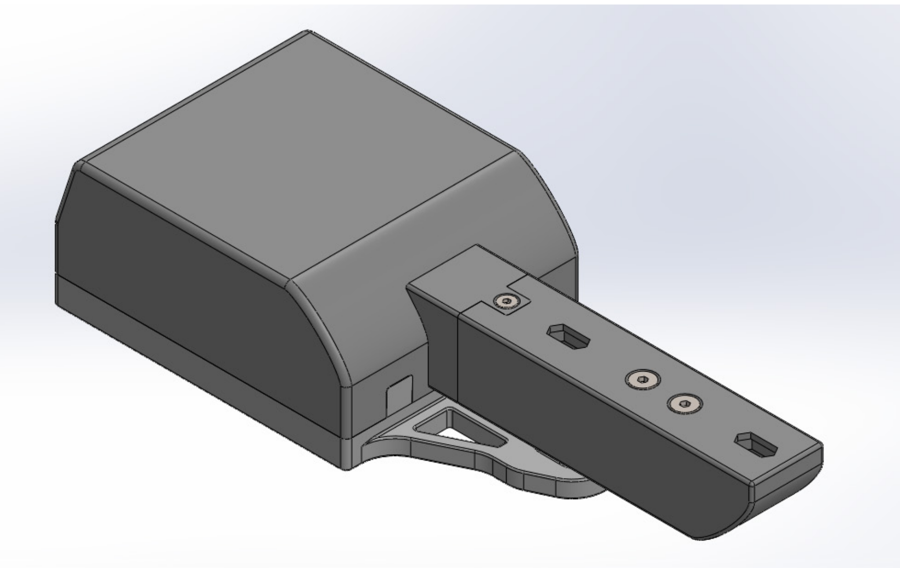
In summary, the firmware of the second prototype represents an incremental and deliberate evolution of the previously validated system. Starting from a stable software base developed under static conditions, the code was progressively adapted to address the additional complexity introduced by real bicycle integration. The shift from wired serial logging to Wi-Fi-based data visualization is not merely a technical upgrade, but a design decision aimed at improving data quality and experimental fidelity, while laying the groundwork for future on-field applications.

Calibration and experimental results on bike

Once the mechanical and electronic integration of the system on a complete bicycle was finalized, I made a new calibration phase was carried out directly in real-use configuration. Unlike previous calibrations—performed on a test bench or under quasi-static conditions—this procedure included the entire system as mounted on the bicycle, comprising frame, mounting interfaces, cabling and bottle cage. The aim was to assess sensor behavior in a configuration as representative as possible of actual use, minimizing idealized assumptions.

Figures 10-11-12: Hardware and layout of Prototype 2.





Initial measurements performed without compensation showed an average offset of approximately 2.3 g. This error can be attributed to the combined effect of the system's own weight, assembly tolerances and residual sensor offset. To compensate for this effect, a TARE function was implemented and activated with the system fully mounted on the bicycle. This allowed the measurement to be zeroed with respect to the real mounting configuration, effectively eliminating the initial offset and aligning the sensor output with that of a reference scale. The introduction of this function resulted in a significant improvement in overall measurement accuracy.
Calibration was performed using 13 experimental points, covering a measurement range consistent with the operational volume of a standard cycling bottle. Data analysis led to the definition of a linear regression model, expressed as:

$$grams=-881.87+1189.63*mV$$

The linear fit shows excellent correlation quality and a highly linear sensor response within the considered working range. The residual root mean square error (RMSE) is approximately ±2.9 g, while the maximum observed absolute error is about ±6.1 g, corresponding to less than 1% of the full scale. These results confirm that the system provides a level of accuracy fully compatible with the application goals of the project (Doebelin & Manik, 2011).

A particularly relevant outcome is the stability of the sensor response in the voltage range between approximately 0.75 mV and 1.25 mV, with no evidence of saturation or signal discontinuities. This behavior was observed despite the system being mounted on a real bicycle and therefore exposed to surface irregularities and micro-vibrations. Experimental observations suggest good robustness of the measurement chain—comprising load cell, mechanical support and software filtering—against high-frequency disturbances, which are effectively attenuated before affecting the output signal (Lyons, 2011).

Some structural limitations nonetheless remain. In particular, the absence of an accelerometer actively integrated into the measurement model, as well as the lack of a dedicated orientation sensor, results in a dependency of the measurement on bicycle inclination and road gradient. Variations in bicycle attitude modify the component of gravitational force projected along the sensitive axis of the load cell, introducing systematic errors that are not compensated at this stage. Despite this, the system shows a generally stable response during riding on uneven surfaces, indicating that the dominant source of error is related to global orientation changes rather than local vibrations.

The continuous tracking function of fluid volume over time, although implemented, still exhibits significant inaccuracies and cannot yet

be considered as reliable. This outcome is consistent with the results obtained in previous dynamic tests and confirms that, while instantaneous weight measurement is now robust, accurate reconstruction of intake evolution over time requires further development—particularly at the algorithmic level and in terms of sensor fusion strategies.
Overall, the results obtained in this phase can be considered positive. The system demonstrates the ability to measure bottle weight with adequate accuracy and linearity directly on a complete bicycle. This represents the first fully functioning prototype of the system and provides a concrete and credible foundation for the optimization and future development phases discussed in the following chapter.

Discussion and design implications

The results obtained with the prototype described in this chapter represent a key milestone in the development of the project. For the first time, the fluid intake monitoring system was integrated on a real bicycle and demonstrated the ability to produce coherent, repeatable and sufficiently accurate measurements under conditions close to actual use. The prototype can therefore be considered successful: the measurement principle is sound, the sensing chain is stable, and the hardware–software architecture is capable of supporting the primary objective of the project.

At the same time, a system-level analysis clearly shows that this prototype still represents a preliminary stage from a product perspective. Design decisions were primarily driven by the need to validate system functionality and to understand signal behavior in real conditions, rather than by formal or aesthetic optimization. As a result, the prototype remains immature with respect to several key requirements of a cycling component intended for real-world use, particularly in terms of overall volume, weight and visual integration.

The geometry of the sensor, strongly dictated by functional constraints and by the physical dimensions of the electronic components, is not yet optimized from either an aerodynamic or perceptual standpoint. Similarly, mass distribution and the presence of relatively bulky elements—such as the load cell and the microcontroller—make the system uncompetitive when compared with the standards of high-performance road cycling.

These limitations do not represent a weakness at this stage of the project, but rather clearly define the boundary between a functional prototype (Figure 13) and a mature product. This prototype therefore serves a precise role: it is not an endpoint, but a validation platform on which the next step can be built. The results allow the focus to shift from the question of whether the system works to the question of how it can be redesigned to comply with the constraints of high-performance road cycling.

Within this framework lies the development of a subsequent prototype oriented toward stronger formal and aerodynamic integration (here referred to as Prototype 2 – Aero), which is introduced as a future direction without being fully developed within the scope of this thesis.

Another relevant outcome of this phase concerns the potential value of the data produced by the system, rather than its immediate use. Although signal processing in this thesis was intentionally kept at a controlled level—consistent with the author's background and project objectives—the measured values open the door to much deeper forms of analysis.

In such a scenario, bottle weight would no longer be an isolated measurement, but a time-dependent variable to be correlated with other key performance parameters, including power output, heart rate, cadence, elevation and training load. This would enable the reconstruction of a temporal profile of hydration and carbohydrate intake, allowing observation of how intake is distributed during activity and how it varies in relation to intensity changes, elevation profiles or environmental conditions. In particular, the possibility of correlating real intake data with defined performance intervals would allow a more objective investigation of the relationship between nutritional strategy and performance response.

In conclusion, the prototype presented in this chapter represents the first fully operational system of the project and provides concrete evidence of the feasibility of the proposed approach. Its limitations in terms of weight, volume and aesthetics do not diminish its value; rather, they define its role within the design process—as a necessary functional demonstrator enabling the transition toward a more advanced, product-oriented development phase, aligned with real competitive constraints.

Figure 13: Prototype 2 mounted on a gravel bike for tests validation.

4.8 Design intent and product-driven approach

Prototype 2 – Aero was conceived as a direct evolution of the first fully functioning prototype, but with a fundamentally different objective. Rather than focusing on the functional validation of the measurement system, this phase aims to translate the concept into a component compatible with high-performance road cycling. At this stage, the project explicitly shifts from an experimental logic to a product-oriented one, where the system must confront strict constraints related to volume, weight, aerodynamics and aesthetics.

The primary intent of this second prototype is a significant reduction of overall size and system mass, while preserving a level of data quality that remains adequate for the intended application. Unlike the first prototype—whose form was largely dictated by function and by the physical dimensions of off-the-shelf components—Prototype 2 was developed starting from the final use context: a contemporary road bike frame, characterized by aerodynamic tube sections, strong component integration and a clean, coherent formal language.

Within this scenario, the sensor can no longer be perceived as an external technical add-on. Instead, it must become an integral part of the bike–bottle cage system. This requirement led to a complete reconsideration of the internal architecture and of the technological choices adopted so far, accepting from the outset that some solutions which were optimal from a purely functional perspective would need to be rethought or replaced in order to meet constraints of integration, lightness and formal coherence.

The design process guiding Prototype 2 is therefore structured around three main directions:

- Reduction of volume and weight, through a revised selection of internal components and a more compact architectural layout;

- Aerodynamic improvement, by aligning the system geometry with the typical cross-sections and flows of modern road bike frames;

- Aesthetic coherence, understood as visual and formal continuity with the frame and components of contemporary high-performance road bicycles.

This phase marks a clear change of scale within the project. The problem is no longer simply measuring correctly, but measuring in a way that is credible within a high-performance product. Prototype 2 is not intended to replace the previous prototype, but to demonstrate how the validated results can be translated into a more mature product vision, while remaining fully aware of the compromises that such a transition inevitably introduces.

Sensor and mechanical architecture

The main evolution I introduced in Prototype 2 – Aero concerns the sensor and mechanical architecture of the measurement system. At this stage, the single load cell adopted in the previous prototype was replaced by two beam-type load cells, similar to those commonly used in consumer-grade weighing devices such as kitchen scales. This sensor family was selected primarily for its reduced volumetric footprint and lower mass, both of which are critical requirements for a system oriented toward aerodynamic integration and product-level constraints (SparkFun Electronics, n.d.).

The two load cells are designed to operate as a coupled system. However, it is important to emphasize that this configuration does not simplify the measurement problem (Images 14 and 15); rather, it increases its complexity from both a mechanical and signal-processing standpoint. Unlike a single load cell, where the applied load is measured along a well-defined axis, a dual-cell architecture requires the system to correctly interpret the distribution of forces across two independent sensing elements. In the presence of mechanical tolerances, assembly misalignments, structural flexion or eccentric loading, the two cells may experience different stress states, leading to discrepancies in their outputs (National Instruments, n.d.).

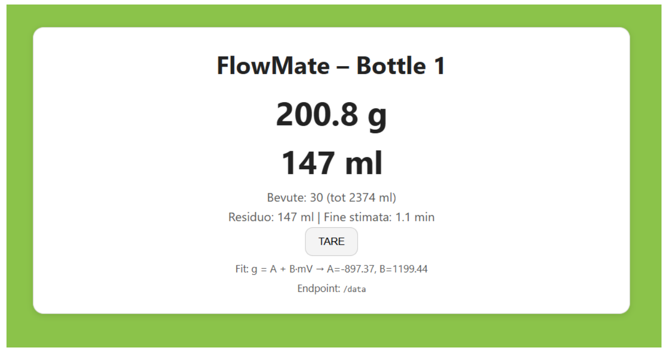
The resulting measurement is therefore not a simple sum of the two readings, but a function of how the load is shared between them. This architecture introduces increased sensitivity to several factors, including:
(i) differences in sensitivity between the two cells;
(ii) asymmetries introduced during mounting;
(iii) local variations in structural stiffness;
(iv) bending moments generated by bottle orientation and load eccentricity.

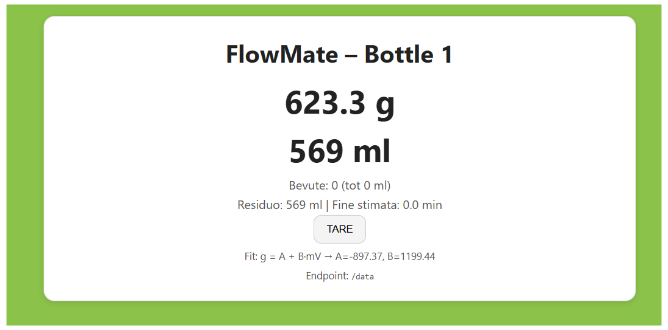
As a consequence, system calibration becomes more involved than in a single-cell configuration, as it must account not only for absolute load values but also for the relative coherence between the two measurements (National Instruments, n.d.).
Despite this added complexity, the adoption of a dual load-cell architecture was considered project-wise justified in light of the objecti-

ves of Prototype 2. From a mechanical standpoint, distributing the load across two sensing points allows a significant reduction in overall height and thickness of the supporting structure, eliminating the need for a rigid and volumetrically dominant central beam. This enables a flatter geometry that can be more easily integrated along the aerodynamic surfaces of modern road bike frames, with a positive impact on volume, mass, and formal integration.

This choice must also be interpreted in relation to the dynamic nature of the cycling context. In real riding conditions, the forces applied to the bottle cage are never constant or perfectly aligned. Changes in slope, longitudinal and lateral accelerations, road-induced vibrations, and micro-movements of the bottle generate continuous load fluctuations that can easily reach several tens of grams over short time intervals. In such conditions, a single load cell tends to translate localized bending moments or eccentric loads into spurious signal variations.

By contrast, a dual-cell configuration distributes the applied load over two sensing points, reducing stress concentration and improving the overall mechanical stability of the system. However, this benefit comes at the cost of increased sensitivity to inter-cell mismatch. Even small differences in sensitivity—on the order of 1–2%—can propagate into measurable deviations in the reconstructed load if not properly compensated. Numerically, this implies that minor relative errors at the sensor level may accumulate when the system is used to reconstruct progressive variations in bottle content over time.





Figures 14 and 15: Desktop user interface for reading data.

This level of complexity was deemed acceptable when evaluated against the type of information required by the final user. For performance engineers and coaches, the primary value lies not in gram-level absolute accuracy at each instant, but in the ability to observe coherent temporal trends in fluid and carbohydrate intake, and to relate these trends to power output, heart rate, cadence, or elevation profile. Within this context, a limited absolute error—on the order of a few grams—is secondary to signal repeatability and long-term stability.

The dual load-cell architecture therefore shifts the focus from maximizing local accuracy to ensuring system-level robustness. The system is not designed to eliminate every possible source of error, but to keep error magnitudes compatible with real-world use and with the decision-making processes the data are intended to support. This reflects a core principle of the project: data quality is defined not only by sensor precision, but by the relationship between information content, usage context, and design constraints.
In other words, Prototype 2 deliberately accepts an increase in measurement complexity in exchange for improved product compatibility. While the first prototype prioritized metrological simplicity and signal clarity, the second prototype shifts the focus toward integration, compactness, and formal optimization, while maintaining data quality within a range considered sufficient for the intended application.

This trade-off is characteristic of high-performance sports product design, where the technically simplest solution is not necessarily the most appropriate in real conditions. The dual load-cell architecture is therefore not intended to maximize absolute precision, but to make measurement possible where integration would otherwise be infeasible within an aerodynamic cycling component.

Hardware architecture and PCB integration

The redesign of the hardware architecture for Prototype 2 – Aero was driven by the need to achieve a substantial reduction in volume, thickness, and geometric complexity, while preserving an electronic platform capable of reliably managing the measurement system. Within this context, the choice of microcontroller represented a critical design decision, as it directly affects both the PCB footprint and the mechanical integration of the overall system.

Compared to the previous prototype, which was based on the ESP32-WROOM module, Prototype 2 adopts an ESP32-C3 microcontroller. This device was selected primarily for its more compact form factor and for a feature set that more closely matches the actual requirements of the system. From a dimensional standpoint, the difference between the two platforms is significant in product-design terms: a typical ESP32-WROOM-32 module measures approximately 18 × 25 × 3.5 mm, whereas the ESP32-C3-WROOM occupies about 18 × 20 × 3.2 mm. Even more compact variants, such as “mini” versions, can reach dimensions as small as 13.2 × 16.6 × 2.4 mm (Espressif Systems, 2023a, 2023b). Although this reduction may appear modest in absolute terms, it translates into a meaningful decrease in PCB area and, more importantly, into increased freedom in three-dimensional component placement.

The ESP32-C3 offers lower computational capability compared to the ESP32-WROOM, which relies on a more complex architecture and greater processing resources. However, the operations required at this stage of the project—namely signal acquisition from the load cells, basic filtering, application of calibration models, and communication handling—do not demand high computational throughput. As a result, the ESP32-C3 represents a functionally appropriate and proportionate choice, avoiding the inefficiency of an over-dimensioned platform (Espressif Systems, 2023b).

A dimensional advantage of the microcontroller had a direct impact on the design of the custom PCB, which was entirely hand-assembled. The PCB was conceived not only as an electrical backbone, but also as a spatial organizer for the internal architecture. To maximize volumetric efficiency, components were soldered on both the top and bottom sides of the board, allowing the electronics to be concentrated within a reduced thickness. This approach inevitably increases assembly and debugging complexity, but it was consciously accepted in pursuit of overall volume reduction and improved aerodynamic integration.

Within this compact architecture, an inertial measurement unit (IMU) was also integrated and positioned in the front section of the system, close to the sensing area. To minimize vertical encumbrance, the IMU was mounted using horizontally oriented pins subsequently bent at 90 degrees. This mounting strategy further reduces the overall profile of the system and improves alignment with the external surfaces of the sensor housing. This choice highlights how, at this stage of development, component-level mounting decisions play a decisive role in achieving compactness and formal coherence.

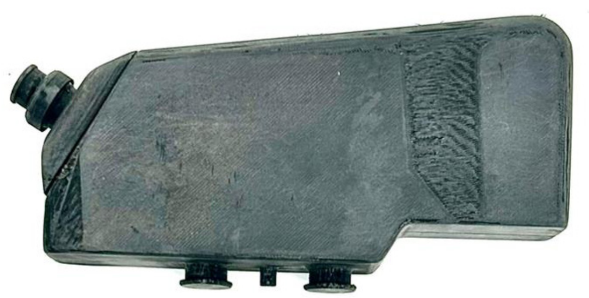


Figure 16: Prototype 2 -Aero bottle design.

Regarding power supply, Prototype 2 employs a 240 mAh battery, identical to that used in the previous prototype. Maintaining the same battery capacity allows the effects of architectural changes on volume and component distribution to be isolated, without introducing additional variables at this experimental stage. Moreover, the selected capacity is consistent with a prototyping phase in which system validation takes precedence over autonomy optimization (Texas Instruments, n.d.).

Overall, the hardware architecture of Prototype 2 represents a clear step toward a more compact, ordered, and product-consistent configuration. The combination of a smaller microcontroller, a densely populated double-sided PCB, IMU integration, and a deliberate approach to power management demonstrates how the system can evolve from a functional demonstrator into a technologically integrable platform. Crucially, this evolution addresses constraints of weight, volume, and integration without compromising the core functionality of the measurement system, reinforcing the feasibility of translating the concept into a high-performance cycling component.

Firmware adaptation and system integration challenges

The evolution of the hardware architecture in Prototype 2 – Aero required a substantial revision of the firmware, which was now tasked with managing a system that is both more complex and less idealized than the previous prototypes. At this stage, software no longer plays a purely instrumental role limited to data acquisition and conversion. Instead, it becomes a central coordinating element, responsible for handling multiple sensors, compensating for mechanical instabilities, and preserving a minimum level of signal coherence within a product-driven and highly constrained configuration.

The first source of complexity arises from the introduction of dual load cells. Unlike a single-sensor configuration, the firmware must now acquire two independent signals, synchronize them temporally, and combine them into a single estimate of the applied load. This process introduces several challenges, including differences in sensitivity between the cells, distinct offsets, uncorrelated noise, and asymmetric load distributions. A simple summation of the two readings proves insufficient if not accompanied by compensation logic, as eccentric loads or small mechanical shifts can generate transient imbalances that are difficult to interpret robustly.

This complexity is further increased by the integration of an inertial measurement unit (IMU), introduced to provide information on system orientation and acceleration. From a firmware perspective, this requires handling data streams with markedly different characteristics: quasi-static signals from the load cells and high-frequency dynamic signals from the inertial sensor. Although, at this stage, IMU data are not yet

actively used to compensate the weight measurement, their presence imposes a more articulated software structure and anticipates future sensor-fusion strategies. Such strategies would require more advanced filtering models and tighter temporal synchronization between sensing modalities.
In parallel with firmware development, Prototype 2 – Aero introduces a radical integration choice from a product-design standpoint. In order to achieve a more coherent, compact, and aerodynamically integrated form, the system was reconceived as a dedicated bottle-cage platform, housing all electronic components internally, paired with a bottle specifically designed for the project. In this configuration, the bottle is no longer a standard consumable element, but an integral part of the measurement system itself.

The constraint between bottle and bottle cage was inspired by magnetic–mechanical coupling solutions, in which guided and rapid attachment replaces the traditional friction-based retention mechanism. While this approach offers clear advantages in terms of user experience and formal integration, it introduces significant technical challenges for a load-based measurement system.

Specifically, the guided magnetic coupling makes the system intrinsically less mechanically stable than a conventional bottle cage. Functional clearances, the need to allow rapid disengagement, and variability in magnetic retention forces generate continuous micro-movements between the bottle and its support. From a firmware perspective, these instabilities translate into signal fluctuations that are difficult to distinguish from actual variations in fluid content. Moreover, the combination of dual load cells, magnetic constraint, and highly integrated geometry amplifies the effects of eccentric loads and bending moments, making the measurement particularly sensitive to small changes in system alignment.
The technical difficulties encountered at this stage—including signal instability, temporal drift, and the inability to achieve robust calibration under dynamic conditions—prevented the system from reaching full measurement reliability. However, it is essential to emphasize that this outcome is consistent with the objectives of this phase of the project. The purpose of Prototype 2 – Aero was not to re-demonstrate the feasibility of the measurement principle, already validated in the previous prototype, but to explore the limits of integration between sensing and product design when constraints related to form, aerodynamics, and user experience become dominant.

In this sense, the firmware developed for Prototype 2 should be interpreted as a first attempt to adapt measurement logic to a highly integrated and non-ideal system. The issues that emerged are not a failure of the approach, but rather a clear mapping of the challenges that must be addressed to transform a functional demonstrator into a truly usable product. These aspects are taken up in the following subsection, where Prototype 2 is analyzed primarily as an exercise in design inte-

Form design and mechanical concept

The development of Prototype 2 – Aero required a dedicated reflection on form design and on the mechanical interface between bottle and bottle cage, which at this stage become as central to the project as electronics and firmware. Unlike the previous prototype, where form largely emerged as a consequence of functional constraints and component dimensions, Prototype 2 adopts an approach in which form, mechanism, and measurement system are conceived as a single, interdependent entity.

The bottle–cage coupling concept draws inspiration from reference systems currently available on the market, such as those developed by Fidlock, which are known for guided interfaces that enable fast, intuitive, and repeatable engagement (Fidlock GmbH, 2023). In the context of this thesis, however, this principle is reinterpreted without the use of magnets, which are replaced by a purely mechanical solution based on constraining geometries and controlled mating surfaces. This choice was driven both by considerations related to constructive simplicity and by the need to avoid unwanted interference with the load-based measurement system.

The aero bottle (Figure 16) was designed as an integral part of the system, rather than as a standard consumable component. From a manufacturing perspective, the bottle body is conceived to be produced through blow molding, a process widely adopted in the sports bottle industry due to its ability to generate lightweight, thin-walled, and mechanically robust geometries with controlled and continuous thickness (Rosato, Rosato, & Rosato, 2000; Osswald & Turng, 2014). This process also offers sufficient formal freedom to design aerodynamic sections and surfaces that integrate coherently with the bicycle frame. The cap and nozzle, by contrast, are conceived for injection molding, in line with established industrial practices for components requiring higher dimensional precision and wear resistance (Goodship, 2017).

Load transfer within the system occurs through two structural pins integrated into the bottle, which act as the primary points through which the weight of the liquid is discharged. These pins are designed to interface directly with the bottle cage and to channel the mass of the fluid toward the two load cells integrated in the system. Between the bottle shell and the contact points, flexible TPU membranes are introduced on the external surface. These membranes allow controlled deformation under load, a strategy commonly adopted in mechanical systems where compliance is required to decouple rigid constraints from sensitive measurement elements (Ashby, 2011).
From a mechanical standpoint, this architecture introduces a delicate balance. The system must satisfy two opposing requirements: on one hand, the bottle must be securely retained to prevent unintended mo-

vement during riding; on the other hand, controlled micro-displacements must be allowed so that the TPU membranes can deform and enable load sensing. Similar trade-offs between constraint, compliance, and stability are well documented in the design of precision mechanical interfaces subjected to dynamic loading (Norton, 2019).
The form design of Prototype 2 therefore emerges as a balance between aesthetic integration, mechanical functionality, and metrological necessity. At this stage, the objective is not to fully resolve all system-level issues, but to explore a formal configuration that makes it conceptually possible for a rapid interface, a visual language coherent with modern road cycling, and an integrated measurement system to coexist.
The design of Prototype 2 – Aero was developed with the explicit goal of achieving visual continuity between bottle cage and bottle, so that they are perceived as a single integrated body rather than as two distinct components. This approach aligns with contemporary aerodynamic design strategies in road cycling, where the reduction of geometric discontinuities is used to limit flow separation and local turbulence (Kyle & Burke, 1984; Blocken, 2018).

In this configuration, the bottle cage is designed to operate exclusively on the down tube of the frame. This choice derives from the observation of contemporary road bike frames, where the down tube typically offers the largest cross-section and the greatest freedom for volumetric integration. Restricting the system to a single mounting position allows the form to be optimized more aggressively and coherently, avoiding compromises required to ensure compatibility across multiple locations. This specialization-over-versatility approach is consistent with design strategies adopted in high-performance integrated cycling systems (Canyon Bicycles, 2022).

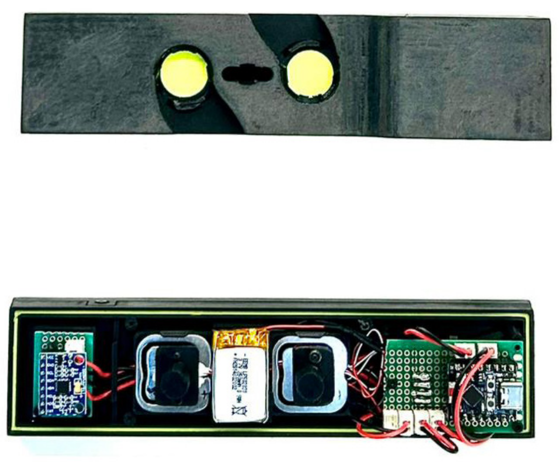


Figure 17: Prototype 2 -Aero hardware layout

4.9 Materials selection and manufacturing

Material selection for Prototype 2 – Aero was conducted following an engineering-driven approach, considering mechanical properties, behavior under cyclic loading, density, compatibility with industrial manufacturing processes, and functional constraints imposed by the measurement system. Each plastic component was associated with a material whose quantitative behavior is consistent with the structural and functional role it performs within the product.

Bottle body – Polyethylene (PE), blow molding

The bottle body is designed to be manufactured in polyethylene (PE), typically HDPE or LDPE, using a blow molding process. Polyethylene exhibits a density in the range of approximately 0.91–0.96 g/cm³, making it particularly suitable for lightweight components with a favorable strength-to-weight ratio (Ashby, 2017). Its elastic modulus, typically between 0.2 and 1 GPa, allows for sufficient elastic deformation to absorb impacts and localized stresses without brittle failure.
From a functional standpoint, the ability of PE to tolerate local deformations is consistent with the system architecture, which requires a non-rigid transmission of the load toward the measurement points. Blow molding also enables the production of wall thicknesses typically in the range of 0.5–1.0 mm, ensuring low mass, material continuity, and significant freedom in shaping aerodynamically driven surfaces (Rosato & Rosato, 2011).

Bottle cage and main structural frame – Nylon (PA), injection molding

The bottle cage and the primary load-bearing structure were conceived in nylon (polyamide, PA), an engineering polymer widely adopted for structural components subjected to cyclic loads. Nylon typically exhibits a density of approximately 1.10–1.15 g/cm³, an elastic modulus in the range of 2–3 GPa, and tensile strength values between 60 and 80 MPa, making it suitable for sustaining the dynamic stresses generated during cycling use (Strong, 2006).
These properties allow the structure to achieve sufficient stiffness to ensure mechanical stability while avoiding excessive deformation that would compromise measurement repeatability. Moreover, nylon's compatibility with injection molding enables the realization of complex geometries, structural ribs, and tight tolerances, all of which are essential for reliable integration with the bicycle frame and the sensing architecture.

Bottle cap – Tritan™ copolyester, injection molding

The bottle cap was designed in Tritan™ copolyester, a BPA-free material commonly used in high-performance food-contact applications. Tritan exhibits a density of approximately 1.18 g/cm³, an elastic modulus in the range of 2.0–2.4 GPa, and tensile strength values typically exceeding 60 MPa, ensuring good stiffness and dimensional stability (Eastman Chemical Company, 2020).

These characteristics make it particularly suitable for components requiring precise geometry, chemical resistance, and long-term durability. Injection molding allows for accurate mating surfaces and a reliable sealing interface, which are critical for both safety and user experience.

Sealing gasket and nozzle – Silicone, compression or injection molding

The sealing gasket and nozzle are conceived in silicone, an elastomer characterized by a very low elastic modulus (approximately 0.005–0.05 GPa) and high elastic deformation capability. Silicone can withstand elongations exceeding 200–300% without significant degradation of mechanical properties, making it ideal for components subjected to repeated compression–release cycles (Bhowmick & Stephens, 2001).
Functionally, these properties ensure reliable sealing performance and consistent tactile feedback, while maintaining stability across a wide temperature range. Silicone is compatible with both compression and injection molding processes, which are commonly employed for precision elastomeric components.

Load transfer membranes – TPU, injection molding or thermoforming

The flexible membranes responsible for load transfer are designed in thermoplastic polyurethane (TPU), a material combining elasticity with mechanical robustness. TPU typically exhibits a density of 1.10–1.20 g/cm³, an elastic modulus ranging from approximately 0.02 to 0.2 GPa depending on formulation, and tensile strength values that can exceed 30–50 MPa, with excellent fatigue resistance (BASF, 2019).

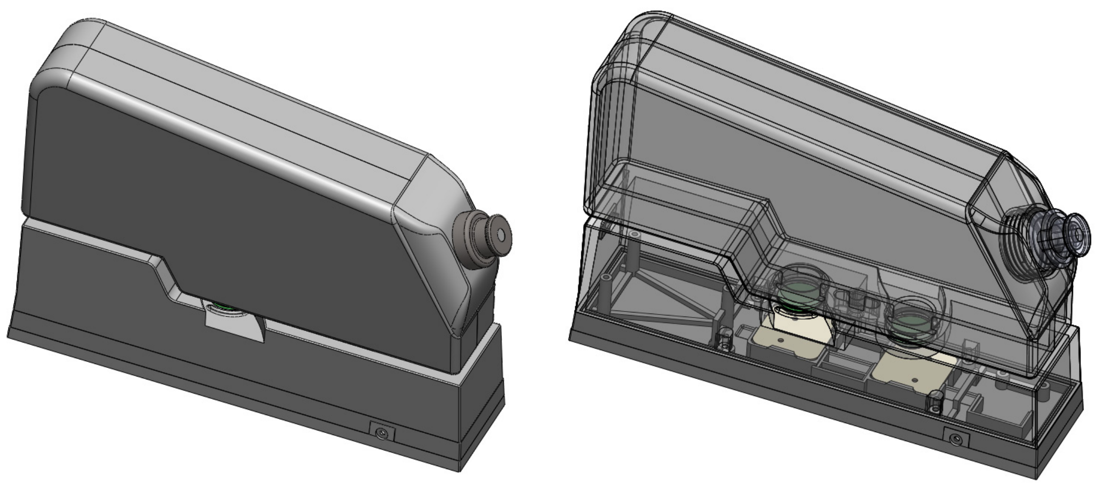


Figure 18 and 19: Prototype 2 - Aero layout design

These properties allow the membranes to undergo cyclic bending under load, transmitting mass to the load cells without introducing excessive hysteresis or structural degradation. Compatibility with injection molding and thermoforming enables precise and repeatable integration of the membranes within the system.

Summary

Overall, material selection for Prototype 2 – Aero (Figures 18 -19) followed a quantitative and function-driven rationale, informed by benchmarking against existing solutions in the cycling industry. Density, elastic modulus, and mechanical strength were evaluated in relation to expected loads and the specific requirements of the measurement system. The selected materials are compatible with established industrial manufacturing processes and position the project within a realistic development scenario, while retaining the flexibility appropriate to an advanced prototyping phase.

4.10 Comparison between Prototype 1 and Prototype 2

The comparison between Prototype 1 and Prototype 2 – Aero represents a key step in understanding the evolution of the project and the shift in priorities that guided the different development phases. The two prototypes should not be interpreted as sequential versions of the same object, but rather as responses to different design questions, positioned at distinct levels of the design and engineering process.
Prototype 1 was developed with a predominantly functional and metrological objective: to verify the feasibility of directly measuring liquid intake during real cycling activity. At this stage, priority was given to data quality, measurement repeatability, and validation of the physical principle underlying the system. Design decisions—such as the use of a single load cell, a relatively rigid mechanical structure, and larger overall volumes—were driven by the need to reduce the number of variables and simplify system behavior. The outcome was a functionally reliable prototype, capable of producing coherent measurements even under moderately dynamic conditions, but poorly aligned with the constraints of integration, weight, and aesthetics required for a high-performance cycling product.
Prototype 2 – Aero, by contrast, was conceived with an explicitly product-oriented objective. In this phase, measurement accuracy is no longer the sole evaluation criterion, but becomes one element to be balanced alongside formal integration, aerodynamics, ergonomics, and industrial plausibility. The introduction of a dual load-cell architecture, the redesign of the electronic system, the reduction of volumes, and the integration of a dedicated bottle represent choices that increase system complexity while enabling exploration of a configuration much closer to a real product scenario.

Prototype 2 exhibits clear limitations when compared to Prototype 1, particularly in terms of signal stability and ease of calibration under dynamic conditions. However, these limitations should not be interpreted as a project failure. On the contrary, they represent a meaningful design outcome, as they highlight the intrinsic difficulties of embedding a measurement system within a cycling component constrained by form, aerodynamics, and user interaction. In this sense, Prototype 2 plays an exploratory and critical role, exposing the trade-offs that emerge when transitioning from technical validation to product design.
Beyond conceptual and qualitative differences, the comparison between Prototype 1 and Prototype 2 – Aero can also be examined quantitatively, showing how the shift in objectives directly affected measurement performance, system volume, and overall complexity.

From a metrological standpoint, Prototype 1 demonstrated higher measurement stability, with average errors in the range of ±2–3 g and a maximum error below 1% of full scale, even under moderate dynamic conditions. This performance was enabled by a simplified architecture based on a single load cell and a more rigid mechanical structure, which limited the number of interacting variables and facilitated calibration.
Prototype 2, while maintaining comparable theoretical sensor resolution, introduces greater signal variability under real conditions. The presence of two load cells, combined with more complex mechanical constraints and functional micro-movements, results in more pronounced short-term fluctuations, making dynamic calibration more critical. At this stage, instantaneous error is higher than in Prototype 1, although it remains acceptable for analyzing intake trends over longer time scales rather than for precise instantaneous measurements.

Prototype 2 achieves a significant reduction in overall size. The adoption of a smaller-footprint microcontroller, a compact double-sided PCB, and an integrated mechanical architecture enables a reduction in electronic volume and a more efficient mass distribution. This transition is essential for approaching the constraints of a realistic cycling product, even at the cost of increased technical complexity.
In terms of system complexity, Prototype 1 can be described as a low-complexity system, where hardware, firmware, and mechanics are clearly separated and optimized for measurement. Prototype 2, in contrast, represents a high-complexity system, in which sensing, form, and user interaction are tightly interdependent. This increase in complexity is not a side effect, but a direct consequence of the product-oriented ambition of the second prototype.

In summary, the comparison between the two prototypes reveals a clear design trajectory: from a functional demonstrator to an integrated product concept. The value of the project does not lie in replacing one prototype with the other, but in their complementarity, which allows the work to span the full spectrum of design engineering—from measurement to form, from engineering validation to product vision.

5.0 Conclusions and Future Developments

5.1 Research outcomes and contribution

The presented in this thesis originated from a practical and, in many ways, simple question: whether it is actually possible to measure fluid intake directly during real high-performance cycling activity, rather than estimating it through indirect models or assumptions. Addressing this question required moving beyond theoretical considerations and confronting the physical, mechanical, and behavioral constraints of real-world use.

The main outcome of this work is the validation of a direct measurement principle based on load cells integrated into a bottle cage system. Through the development of Prototype 1, it was possible to obtain stable and repeatable measurements, with linear sensor behavior and average errors on the order of a few grams, even under dynamic conditions. This result is particularly relevant because it demonstrates that intake can be measured without relying on planned strategies, post-hoc reconstruction, or manual input from the athlete.
At the same time, this work made it clear that measurement accuracy cannot be interpreted in isolation.

What emerged during testing is that the temporal structure of intake, rather than absolute precision alone, represents the most meaningful layer of information when correlated with power output, heart rate, and terrain. From my perspective, this represents a significant contribution: it shifts the focus from “how much was consumed” to “when and how intake evolved during performance”.

A further contribution of this thesis lies in the deliberate exploration of integration limits. Prototype 2 – Aero did not reach the same level of measurement stability as the first prototype, and this was initially frustrating. However, it quickly became evident that this outcome was not a failure, but one of the most informative results of the entire project. It revealed, in a tangible way, the tension between metrological reliability and product-level constraints such as volume, aerodynamics, and user interaction.

Overall, the contribution of this work does not reside in a single optimized solution. Instead, it lies in a design engineering process that combines experimentation, iteration, and critical reflection, making explicit the compromises that inevitably arise when a sensing system is translated into a real product context.

5.2 Design engineering perspective

This project can be best understood through a design engineering lens, where solutions emerge from negotiation rather than optimization. Throughout the work, progress was rarely linear: each improvement in one aspect of the system often introduced new constraints elsewhere, requiring continuous reassessment of priorities.

One of the clearest lessons concerns the management of trade-offs. Prototype 1 prioritized measurement stability and clarity of signal, accepting increased volume and reduced integration. Prototype 2 deliberately inverted this balance, pursuing a more realistic product configuration at the cost of measurement robustness. This transition was not accidental, but the result of a conscious shift in design intent.
Another defining aspect of the process was the role of prototy
ping as a means of thinking. Each prototype functioned less as a step toward a final object and more as a tool to answer specific questions. Prototype 1 addressed whether the measurement principle was viable at all. Prototype 2 exposed the consequences of embedding that principle within a constrained mechanical and ergonomic system. In this sense, limitations and partial failures became productive elements of the design process.

Perhaps most importantly, this work highlighted design as an act of selection and renunciation. Several technically feasible options were intentionally excluded to preserve coherence at the system level. Learning when not to pursue a solution proved as important as identifying promising directions, and this represents one of the core outcomes of the design engineering approach adopted in this thesis.
The project also required operating across multiple scales, from sensor behavior and signal processing to system architecture and user interaction. Navigating these scales reinforced the idea that complex systems cannot be addressed through a single disciplinary approach. Instead, meaningful progress emerges when engineering rigor and design judgment inform each other.

5.3 Limitations of the work

The work presented here is characterized by a number of limitations that are important to acknowledge openly. These limitations define the scope of the project and clarify its position as an exploratory rather than definitive solution.

The first limitation concerns measurement robustness in highly integrated configurations. While Prototype 1 showed stable behavior under dynamic conditions, Prototype 2 exhibited increased signal variability due to the interaction between dual load cells, mechanical constraints, and necessary micro-movements. Achieving a calibration strategy capable of compensating for all dynamic effects was beyond the scope of this phase of development.

A second limitation relates to signal processing. Although an inertial measurement unit was integrated, its data were not fully exploited through advanced sensor fusion techniques. Filtering strategies remained intentionally simple, sufficient for validating the measurement principle but inadequate for fully compensating dynamic disturbances.

From an experimental perspective, testing was conducted on a limited set of configurations and did not include systematic validation across multiple athletes or riding styles. As a result, the findings should be interpreted as indicative rather than generalizable.

Finally, the system measures intake but not physiological response. Intake alone cannot describe absorption, gastrointestinal tolerance, or metabolic effects. These aspects lie beyond the capabilities of the current system and require integration with physiological models and additional sensing modalities.

5.4 Future developments

The limitations identified throughout this work naturally suggest several directions for future development. From a technical standpoint, the most immediate step involves improving dynamic stability through tighter integration between load cell data and inertial measurements. Sensor fusion and adaptive filtering represent promising paths to distinguish real mass changes from motion-induced artifacts.

At the product level, further refinement of the bottle–cage interface is required to balance stability, functional compliance, and intuitive handling. Weight and volume reductions through optimized structural design and electronic integration would also be essential to approach real-world deployment.

One of the most relevant opportunities lies in integrating intake measurements with existing performance analysis ecosystems. Synchronizing intake data with power, heart rate, and elevation profiles would enable a richer interpretation of hydration strategies and open new possibilities for individualized performance analysis.
Taken together, these developments would allow the system to evolve from an experimental prototype into a technological platform capable of supporting both research and applied performance optimization.

5.5 Final considerations

This thesis represents for me more than the conclusion of an academic requirement. It is the result of a long process in which personal interest, technical curiosity, and design practice gradually converged into a coherent project.
Alongside my studies in Design Engineering, I pursued a parallel specia-

lization in cycling through Policiclo, where I served as president of the association, and through the founding of POLICRIT. These experiences deeply shaped my understanding of cycling as a system that extends beyond performance alone, encompassing technology, culture, and community. This perspective strongly influenced the direction and motivation of this work.

Throughout the project, I encountered uncertainty, technical setbacks, and decisions that required accepting imperfect outcomes. These moments were fundamental in shaping my understanding of design as a process of learning rather than execution. Measuring, I realized, is only meaningful when paired with interpretation and context.

This work was developed during a transitional phase of my professional path. As I already said in the introduction, I am currently working as an R&D Engineer at Vision FSA, contributing to the development of an electronic shifting system, and many of the challenges faced in this thesis—system integration, reliability, space constraints—are now part of my daily practice. This continuity made it clear to me that the skills developed during this project are not abstract, but immediately applicable.

In this sense, this thesis represents both an ending and a beginning. It marks the conclusion of an academic journey and the start of a professional direction that I intend to pursue with the same curiosity and critical attitude that guided this work.

Figure 20: Test Gravel Bike with Prototype 2, setup for layout validation.

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