

Unlocking Digital Circularity

Socio-Technical Conditions for Actionable Engagement with Digital
Circular-Economy Platforms in Business-to-Business Waste-Value
Ecosystems

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Unlocking Digital Circularity:

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Engagement with Digital Circular-Economy
Platforms in Business-to-Business Waste-Value
Ecosystems

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Preface

This thesis marks the completion of my two-year Master's programme in Engineering and Policy Analysis at Delft University of Technology, a programme that I pursued with curiosity, ambition, and perseverance. That same mindset formed the foundation of this thesis. For my graduation research, I deliberately sought a layered multi-actor problem at the intersection of technical systems, organisational behaviour, and societal transitions. I wanted to study a topic in which systems thinking, policy relevance, data analysis, and the complexity of real-world practice come together. The opportunity to conduct research on organisational engagement with digital circular-economy platforms within a B2B waste-value ecosystem therefore felt both like an honour and a fitting challenge. Writing this thesis was demanding, intensive, and highly instructive. The research required the combination of quantitative data preparation, exploratory analyses, interview-driven inquiry, and theoretical reflection. In particular, the messiness of real-world data and the need to connect different analytical perspectives made the process challenging, but intellectually very valuable.

I would like to express my sincere gratitude to my academic supervisors, Dr. Anneke Zuiderwijk and Dr. Jan Anne Annema, for their guidance, critical feedback, and support throughout this thesis process. I am especially grateful for their willingness to take my ambitions seriously and to guide me at that level. Thank you for your sharp questions, the substantive discussions, and for continuously challenging me to further strengthen my reasoning, structure, and argumentation.

My sincere thanks also go to Milgro, and in particular to Demy Sint Nicolaas, for her openness, practical support, and trust. The collaboration with Milgro helped me connect academic analysis to the real-world context in which these questions actually unfold. I would also like to thank all interviewees who were willing to participate in this research, often at very short notice. I am grateful for the time, openness, and valuable perspectives they shared.

Finally, I would like to thank my parents. They taught me to remain curious, to keep pushing boundaries, and to think in terms of opportunities and possibilities rather than limitations. The mindset they gave me has helped shape how I approached both my studies and this graduation research. I look back on my time at TU Delft with pride. EPA has challenged me to think critically and has taught me to approach complex problems from multiple perspectives. This thesis forms a fitting conclusion to that journey.

*Suus Plaum
Delft, June 2026*

Executive Summary

Resource scarcity, growing waste streams, and increasing environmental pressure make the transition towards a circular economy an urgent societal and organisational challenge. This urgency is reinforced by sustainability reporting requirements, such as the CSRD and related standards. Organisations are increasingly expected to make their waste streams, environmental performance, and circular progress visible.

Digital circular-economy platforms are often presented as important infrastructures for this transition. In business-to-business waste-value ecosystems, such platforms can make waste volumes, separation percentages, waste-related costs, CO₂-related indicators, and location-level differences visible. Yet visibility of waste-related platform data does not by itself constitute circular value creation. Circular value depends on whether residual material flows can be physically separated, classified, collected, processed, and revalorised, often involving actors beyond the waste-producing organisation. Consequently, similar platform information may become connected to circular follow-up in one organisation, while remaining mainly informational, report-oriented, or weakly embedded in another.

Existing literature provides useful but fragmented insights into this issue. Digital circular-economy platform literature highlights the potential of platforms for data exchange and ecosystem coordination. Technology-adoption literature explains how users evaluate digital systems and whether they perceive them as useful and trustworthy. Socio-technical and practice-based information-systems literature shows that technology use depends on routines, responsibilities, and organisational embedding. Digital-circularity literature identifies barriers related to data quality, inter-organisational coordination, interoperability, and ecosystem dependencies. However, limited empirical insight exists into how these conditions interact in practice within business-to-business waste-value ecosystems.

The objective of this thesis is therefore to explain when and how waste-related platform information can contribute to the broader circularity purpose of digital circular-economy platforms. The central research question is:

Under which socio-technical conditions can information within a digital circular-economy platform support organisational action for circular-performance improvement in a business-to-business waste-value ecosystem?

Socio-technical conditions refer to the technological, organisational, and social elements that shape platform use in practice. Organisations refer to the waste-producing client organisations that use the platform to access waste-related information. A business-to-business waste-value ecosystem refers to the wider network of actors involved in the collection, classification, processing, and potential revalorisation of waste streams.

The thesis examines this question through an embedded single-case study of Milgro's digital circular-economy platform ecosystem. Milgro was selected because its platform brings together operational, financial, environmental, and reporting-related waste information in one digital environment. Within this single case, client organisations connected to the platform are treated as embedded units of analysis. This makes it possible to examine variation in platform use and circular-performance indicators across multiple organisations while keeping the platform infrastructure constant.

The study follows a sequential explanatory mixed-methods design. First, a literature-based analytical framework was developed to conceptualise platform use as multidimensional and socio-technical. Second, quantitative platform interaction data and circular-performance indicators from 196 client organisations over the period 2024Q1–2025Q4 were analysed. This phase examined variation in platform engagement and explored whether dashboard use was associated with circular-performance indicators, including waste separation, waste-related costs, and CO₂-equivalent emissions per kilogram of waste. Third, semi-structured interviews were conducted with sixteen client organisations from contrasting engagement-performance profiles. The interviews were used to explain the organisational

meaning behind the quantitative patterns and to examine how waste-related platform information was interpreted, embedded, and followed up in practice.

The quantitative analysis produced two main findings. First, organisational engagement with the Milgro platform was uneven, multidimensional, and context-dependent. Organisations did not simply use the platform more or less. Instead, they differed across four engagement dimensions: informational dashboard engagement, routine transactional engagement, support-related engagement, and non-routine operational engagement. These dimensions did not consistently move together. Organisations that frequently viewed dashboards were not necessarily the same organisations that placed routine waste orders through digital channels, relied heavily on support interactions, or generated many non-routine operational interactions. Dashboard use should therefore not be treated as a proxy for overall platform engagement.

Second, the relationship between informational dashboard engagement and circular-performance indicators was limited and conditional. Relative dashboard intensity, measured as dashboard views per 100 orders, was not robustly associated with waste separation, waste-related costs, or CO₂-equivalent emissions per kilogram of waste after correction for multiple testing. This indicates that frequent dashboard viewing mainly captures access to dashboard information, rather than whether that information is interpreted, embedded, or followed up in organisational practice. Structural dashboard activity, measured as recurring dashboard activity over time, was more informative. Organisations with more structural dashboard activity tended to show higher separation percentages and lower waste-related costs per kilogram in the bivariate analysis. However, these associations weakened when sector and customer-size differences were taken into account. The quantitative findings therefore suggest that consistency of dashboard activity may be more meaningful than viewing intensity alone, but that its relevance depends on organisational and sectoral context.

The qualitative findings helped explain these quantitative patterns. The interviews showed that dashboard information was often perceived as useful, especially for visibility, reporting, monitoring, and accountability. However, perceived usefulness did not automatically imply actionability. Waste-related dashboard information became practically relevant only when users trusted the data, interpreted what the information meant in their operational waste context, and could connect it to possible follow-up.

Four mechanisms were identified that explain why dashboard information moved from visibility to organisational follow-up in some organisations, while remaining mainly informational, report-oriented, or weakly embedded in others.

The first mechanism is contextual interpretation. The interviews showed that dashboard information provided insight, but became practically relevant only when users trusted the data and interpreted what the information meant in relation to their own waste streams, operational processes, sector conditions, and possible improvement options. Changes in waste volume, costs, separation percentages, CO₂-related indicators, or waste-stream classifications rarely explained themselves. They required interpretation before users could assess whether they indicated a performance issue, a temporary operational circumstance, a classification problem, contamination of a waste stream, or a realistic circular improvement opportunity.

Second, dashboard information was often embedded in reporting routines, such as ESG reporting or CSRD preparation, but this reporting embeddedness did not automatically lead to operational routine embedding. Waste-related information became more relevant for follow-up when it entered organisational routines in which deviations were discussed, responsibilities were assigned, and improvement actions could be considered.

Third, a monitoring-action gap was visible in many organisations. The actors monitoring dashboard information were often not the same actors who could change waste-producing practices. As a result, dashboard visibility did not automatically lead to changes in source separation, waste handling, operational routines, supplier conversations, or site-level practices.

Fourth, follow-up was ecosystem-constrained. Even when dashboard information revealed a circular improvement opportunity, client organisations could not always act on it independently. Circular-performance improvement could depend on suppliers, customers, waste collectors, processors,

sector-specific safety or hygiene requirements, or available revalorisation routes. Dashboard transparency therefore did not equal organisational control over action.

By integrating the quantitative and qualitative findings, this thesis refines the literature-based framework into the actionable engagement mechanism. This mechanism explains how waste-related platform information becomes actionable in a business-to-business waste-value ecosystem.

The actionable engagement mechanism consists of five socio-technical conditions across the micro, meso, and macro levels. At the micro level, data confidence and contextual interpretation are required. Users need to trust dashboard information and understand what it means in relation to waste streams, operational processes, sector constraints, and organisational circumstances. At the meso level, operational routine embedding and connected ownership are required. Dashboard information must enter recurring management, operational review, site-level, or improvement routines in which deviations can be discussed and follow-up can be considered. In addition, responsibility must be clear for monitoring, interpretation, decision-making, escalation, and implementation. At the macro level, feasible follow-up is required. Action must be possible within the wider waste-value ecosystem, including collection, processing, regulatory, contractual, and revalorisation options.

The thesis therefore answers the main research question by showing that information within a digital circular-economy platform can support organisational action for circular-performance improvement when platform engagement is converted into actionable engagement. Digital circular-economy platforms do not create circular value through transparency alone. Their value depends on whether waste-related information becomes trusted, contextually meaningful, embedded in operational routines, connected to responsible actors, and feasible to act upon within the wider waste-value ecosystem.

The practical implications follow from this mechanism. For platform providers, dashboards should be designed not only for monitoring and reporting, but also for waste-specific interpretation and action. This can be supported, for example, through clearer indicator definitions, transparent data-status information, sector-specific benchmarks, deviation alerts, explanatory labels, role-specific dashboard views, and links between dashboard signals and possible operational interventions. For client organisations, dashboard use should be connected to routines and responsibilities. Organisations should distinguish between dashboard ownership and action ownership, and ensure that waste-related insights are discussed in operational review cycles, site-level meetings, supplier discussions, or waste-reduction projects. For policymakers and institutional actors, the findings suggest that digital circularity should not be approached only as a transparency or reporting challenge. Reporting obligations can increase the availability of waste-related data, but circular-performance improvement also requires more specific policy support for shared waste classifications, consistent treatment-route definitions, interoperable data exchange between waste-producing organisations, platform providers, collectors, and processors, and ecosystem coordination around feasible processing and revalorisation routes.

The theoretical contribution of this thesis lies in the development of the actionable engagement mechanism. This mechanism integrates insights from existing literature on digital circular-economy platforms, technology adoption, socio-technical information systems, and digital-circularity barriers, and specifies them for the context of circular waste management. By connecting the identified translation gaps to the five conditions of actionable engagement, the thesis explains why similar platform information may support circular follow-up in one organisation, while remaining mainly informational or report-oriented in another.

The study has three main limitations. First, the actionable engagement mechanism was developed within one embedded single-case setting. Although it is analytically transferable to other digital circularity contexts, different platform designs, sectors, governance arrangements, or circularity domains may require further refinement. Second, the qualitative phase used purposive sampling from engagement-performance profiles, which means that the interview findings should not be interpreted as representative of all client organisations within each profile. Third, the quantitative analysis covered the period 2024Q1–2025Q4, making the findings time-bounded. Future research could therefore examine how platform engagement and actionable engagement develop over time and across different platform designs, sectors, and circularity domains. It could also use a broader and more systematically sampled set of organisations to assess how widely the identified mechanisms occur across different

engagement-performance profiles.

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1 | Introduction

1.1. Background: digitalisation and the circular economy

Resource scarcity, growing waste streams, and increasing environmental pressure have made the transition towards a circular economy an urgent societal and organisational challenge. Circular-economy strategies aim to move away from linear resource consumption by closing, slowing, and narrowing resource flows through practices such as reuse, recycling, waste reduction, and improved resource efficiency (Bocken et al., 2019; Charef & Lu, 2021; Körppen et al., 2024). Achieving these ambitions requires more than technical waste-processing capacity. It also requires insight into material and waste flows, coordination between multiple actors, and organisational decision-making based on relevant performance information (Bimpizas-Pinis et al., 2022; Körppen et al., 2024).

Digitalisation is increasingly positioned as an important enabler of the circular transition. Digital technologies can improve data availability, enable real-time monitoring, and facilitate coordination across value-chain actors (Kovacic et al., 2020; Kristoffersen, 2021). Digital platforms are particularly relevant in this regard because they can function as infrastructures through which organisations collect, share, and analyse data on resource flows and circular-economy activities across organisational boundaries (Carlos et al., 2024; Körppen et al., 2024). In this way, digital platforms may support information visibility, coordination, and more informed resource-related decision-making.

This potential is particularly relevant in business-to-business waste-value ecosystems. In such ecosystems, waste-related information and circular-performance improvement depend on interactions between multiple organisations involved in the collection, classification, processing, and potential revalorisation of waste streams (Carlos et al., 2024; Körppen et al., 2024). Digital circular-economy platforms can make these processes more visible by providing information on waste volumes, separation percentages, waste-related costs, CO₂-related indicators, and differences between locations. This information can support monitoring, reporting, and performance evaluation.

However, the availability of digital circularity information does not automatically mean that waste-producing client organisations use this information for operational steering or circular-performance improvement. Organisations may have access to dashboards and performance data while still using them mainly for reporting, accountability, or retrospective monitoring. The organisational value of performance information depends on whether it is interpreted, embedded in decision-making routines, and connected to possible action (Moynihan & Lavertu, 2012; Moynihan & Pandey, 2010). In other words, information availability does not necessarily equal organisational action.

1.2. Problem statement: from information availability to organisational action

The distinction between information availability and organisational action is reinforced by policy developments. Circular-economy policies increasingly emphasise traceability, reporting, accountability, and performance monitoring across waste and material flows (Charef & Lu, 2021; European Commission, 2020). These developments create growing expectations for organisations to demonstrate progress towards more circular resource use. At the same time, policy frameworks tend to emphasise the enabling role of digitalisation and information availability, while providing limited guidance on how digital tools should be adopted, embedded, or used within organisational routines (Barteková & Börkey, 2022; European Commission, 2020). The practical implementation of digital circular-economy tools is therefore largely left to individual organisations, platform providers, and other actors in the waste-value ecosystem (Kristoffersen, 2021; Ndoka, 2023).

This creates a gap between regulatory ambition and organisational practice. Organisations are increasingly expected to monitor waste flows, report on environmental indicators, and improve

circular performance, but they may not yet have the routines, capabilities, or incentives required to transform available data into operational improvements (Ndoka, 2023). In such cases, digital platforms may increase information visibility without necessarily changing organisational behaviour or decision-making. Real-time dashboards may indicate where improvements could be possible, but their practical value depends on whether the information can be understood, trusted, embedded in work processes, and connected to possible follow-up (Besson & Rowe, 2012; Orlikowski, 2000).

The central practical problem addressed in this thesis is therefore that digital circular-economy platforms are increasingly expected to support circular value creation, while access to platform data and dashboards does not automatically translate into organisational action or improved circular performance. This raises the question of how organisations use waste-related platform information in practice, and under which socio-technical conditions this information may become connected to organisational action for circular-performance improvement.

This problem connects to several related literature streams.

1.3. Research gap

Several literature streams are relevant to the research question. Circular-economy platform literature explains that digital platforms may support different forms of interaction and that platform use should therefore not be treated as a single activity. This literature also shows that digital platforms can support coordination, data exchange, information visibility, and circular value creation across ecosystems (Körppen et al., 2024; Petrik et al., 2025).

Technology-adoption literature provides a second relevant perspective. It explains technology use through factors such as perceived usefulness, ease of use, and trust (Davis, 1989; Faiz et al., 2024; Venkatesh et al., 2003). These concepts are relevant because organisational platform use is partly shaped by how users understand, evaluate, and trust digital information. However, they do not fully explain how information becomes connected to organisational action.

Socio-technical and practice-based information-systems literature provides an additional organisational perspective. It shows that technology use gains organisational meaning through routines, roles, responsibilities, and situated practices (Besson & Rowe, 2012; Orlikowski, 2000). Furthermore, digital-circularity literature identifies barriers at organisational and ecosystem levels, including data quality, capabilities, coordination problems, interoperability, and regulatory conditions (Blackburn et al., 2023; Petrik et al., 2025; Trevisan et al., 2023).

Taken together, these literature streams suggest that digital circular-economy platforms differ from many conventional organisational information systems. Their benefits are often collective, data-dependent, delayed, and distributed across multiple actors.

Existing literature therefore offers fragmented insights into platform potential, technology acceptance, organisational embedding, and digital-circularity barriers. However, it remains insufficiently specified how these conditions interact to determine whether waste-related information provided through digital circular-economy platforms becomes connected to organisational follow-up for circular-performance improvement. There is also limited empirical insight into how waste-related platform information is translated into organisational follow-up within business-to-business waste-value ecosystems.

1.4. Research objective

This thesis examines the identified research gap in a business-to-business waste-value context. The objective of this thesis is to understand the socio-technical conditions under which information from a digital circular-economy platform can be translated into organisational action that supports circular-performance improvement and contributes to broader circular-economy objectives.

1.5. Research question and sub-questions

The main research question guiding this thesis is:

Under which socio-technical conditions can information within a digital circular-economy platform support organisational action for circular-performance improvement in a business-to-business waste-value ecosystem?

Socio-technical conditions refer to the interacting technological, organisational, and social elements that shape how a digital system is used and becomes embedded in organisational practice (Bostrom & Heinen, 1977; Orlikowski, 2000). *Organisations* refer to the client organisations connected to the digital circular-economy platform. A *business-to-business waste-value ecosystem* refers to the organisational and inter-organisational context in which these client organisations use waste-related information within a wider network of actors involved in the collection, classification, processing, and potential revalorisation of waste streams.

In this thesis *digital circular-economy platforms* are conceptualised as digital systems that support circular-economy-related monitoring, reporting, coordination, and decision-making. Performance dashboards are treated as one important interface within such platforms. In general, performance measurement systems can support monitoring, feedback, and organisational learning (Barth & Formoso, 2008; Henri, 2006). In this thesis, *performance dashboards* specifically refer to the dashboard interfaces through which client organisations can access information on waste flows, costs, environmental indicators, and circular-performance indicators.

To answer the main research question, four sub-questions are formulated.

1. How does the use of the digital circular-economy platform vary across organisations?

This sub-question maps empirical variation in platform use across organisations. It focuses on differences in the frequency, form, and consistency of observable platform interactions.

2. How is the use of performance dashboards associated with available circular-performance indicators?

This sub-question explores whether dashboard use coincides with differences in circular-performance indicators, such as waste separation, waste-related costs, and CO₂-related impacts.

3. How do organisational users understand, interpret, and evaluate dashboard information?

This sub-question examines how users make sense of dashboard information in their organisational context. It focuses on how users describe the role, meaning, and perceived value of dashboard information.

4. Which organisational and ecosystem-level conditions facilitate or hinder the use of platform information for organisational follow-up within a business-to-business waste-value ecosystem?

This sub-question examines the conditions under which platform information becomes connected, or fails to become connected, to organisational follow-up. It focuses on how internal organisational factors and wider ecosystem factors shape this translation process.

Together, these sub-questions are addressed through a sequential explanatory mixed-methods design within an embedded single-case study, as explained in Chapter 2.

1.6. Scientific, societal, and EPA relevance

Scientifically, this thesis contributes to research on digital circular-economy platforms and information-systems use by examining how waste-related platform information may become connected to organisational action in a business-to-business waste-value ecosystem. Existing literature provides fragmented insights into platform potential, technology acceptance, organisational embedding, and digital-circularity barriers. This thesis brings these perspectives together to analyse the socio-technical conditions under which information from a digital circular-economy platform may become actionable for

circular-performance improvement. Rather than treating platform use as a binary adoption outcome, the study examines platform engagement as a multidimensional organisational practice.

Societally, the study is relevant because digital tools are increasingly used to support circular-economy objectives, waste reduction, and sustainability reporting. However, if organisations use digital circularity information mainly for reporting or retrospective monitoring, the contribution of digitalisation to circular-performance improvement may remain limited. By examining the conditions under which platform information becomes connected to organisational follow-up, the thesis provides insights for platform providers, client organisations, and policymakers concerned with moving digital circularity beyond visibility alone.

From an Engineering and Policy Analysis perspective, the thesis analyses digital circularity as a socio-technical and multi-actor implementation problem. Circular-performance improvement depends not only on digital information systems, but also on organisational routines, actor responsibilities, decision-making structures, and coordination across the wider waste-value ecosystem. This makes the research relevant to EPA because it connects technological information systems with organisational behaviour and policy-relevant implementation challenges.

1.7. Thesis outline

The remainder of this thesis is structured as follows. Chapter 2 explains the research methodology and mixed-methods design. Chapter 3 reviews the relevant literature, and Chapter 4 develops the literature-based analytical framework. Chapter 5 introduces the Milgro case study. Chapter 6 describes the quantitative data preparation and operationalisation, while Chapter 7 presents the quantitative results. Chapter 8 explains the qualitative research design and interview selection, and Chapter 9 presents the qualitative findings. Chapter 10 integrates the findings, answers the main research question, develops the actionable engagement mechanism, and discusses implications, limitations, and directions for future research.

2 | Research Methodology

This chapter presents the research methodology of the thesis. The study combines a structured literature review with an embedded single-case study of Milgro's digital circular-economy platform. The literature review identifies concepts from related research streams and brings them together in a literature-based analytical framework. The empirical study then applies this framework to the Milgro platform ecosystem through a sequential explanatory mixed-methods design.

The methodological approach follows from the objective of the thesis. The study seeks to understand under which socio-technical conditions information from a digital circular-economy platform becomes connected to organisational action for circular-performance improvement. This objective requires both conceptual development and empirical explanation. The conceptual part of the study identifies relevant insights from existing literature. The empirical part examines how platform information is used within a real-life business-to-business waste-value ecosystem.

This chapter is structured as follows. Section 2.1 presents the overall research design. Section 2.2 explains the literature review approach. Section 2.3 discusses the embedded single-case study design. Section 2.4 explains the sequential explanatory mixed-methods design. Section 2.5 provides the case-selection rationale for Milgro. Section 2.6 describes the empirical research flow. Section 2.7 discusses validity, trustworthiness, and methodological limitations.

2.1. Overall research design

The thesis follows a two-part research design. The first part consists of a structured, concept-centric literature review. This review brings together literature on digital circular-economy platforms, technology acceptance and organisational technology use, socio-technical and practice-based information systems, and digital-circularity barriers. The purpose of the literature review is not to present these fields chronologically. Instead, it identifies concepts that help explain how digital platform information can become connected to organisational action.

The second part consists of an empirical embedded single-case study. The empirical case is Milgro's digital circular-economy platform. The embedded units of analysis are the client organisations that use the platform. This design allows the study to examine organisational variation within one shared platform ecosystem. It is suitable because the research problem concerns the use of platform information within organisational and inter-organisational waste-value contexts.

The empirical study uses a sequential explanatory mixed-methods design. In this design, an initial quantitative phase is followed by a qualitative phase that helps explain and contextualise the quantitative results. The quantitative phase maps observable patterns of platform use and explores associations between dashboard information use and circular-performance indicators. The qualitative phase then examines how these patterns may be understood in relation to the socio-technical conditions specified in the literature-based analytical framework.

The design is explanatory rather than causal. The quantitative phase does not aim to prove that platform use causes circular-performance improvement. Instead, it identifies patterns and associations that can be interpreted in light of qualitative evidence and the literature-based analytical framework. This cautious interpretation is necessary because platform use and circular-performance indicators may be mutually related and shaped by broader organisational and contextual conditions.

2.2. Literature review approach

The literature review follows a structured, concept-centric approach, consistent with established guidelines for literature reviews in information systems research (Webster & Watson, 2002). A concept-centric approach is appropriate because this thesis does not aim to provide a chronological

overview of the literature, but to identify and integrate concepts across research streams that help explain how information from digital circular-economy platforms may become connected to organisational action.

The review approach can best be characterised as a systematized review, as described by Grant and Booth (2009). This type of review incorporates elements of systematic searching and transparent selection, while not claiming to be a full systematic review with exhaustive coverage or formal quality scoring. This positioning is appropriate because the aim is to develop a theoretically informed foundation for empirical research rather than to produce a comprehensive evidence map.

The literature search focused on academic work relevant to the problem statement of this thesis. Peer-reviewed literature was identified through Scopus and Google Scholar. These databases were selected because they provide broad coverage of information systems, sustainability transitions, circular-economy research, and organisational studies. Search queries combined three thematically related clusters using Boolean operators.

The first cluster captured the circular-economy context, using terms such as “circular economy”, “waste-value chain”, “waste management”, “resource recovery”, “reverse logistics”, and “circular value creation”. The second cluster focused on digital technologies and platforms, using terms such as “digital platform”, “data platform”, “information system”, “dashboard”, “digital technology”, and “real-time monitoring”. The third cluster addressed organisational adoption and use, using terms such as “technology adoption”, “platform use”, “user engagement”, “organisational routines”, “organisational users”, and “implementation barriers”. These clusters were combined to identify publications at the intersection of digital platforms, circular-economy implementation, and organisational technology use.

Backward and forward citation tracking was applied to identify foundational and highly relevant studies that did not appear directly through the initial search queries (Webster & Watson, 2002). Publications were included when they met three criteria. First, they had to address digital platforms, digital tools, information systems, or data infrastructures in a circular-economy, sustainability, or waste-management context. Second, they had to provide insight into adoption, use, engagement, implementation, value creation, or organisational embedding. Third, they had to be conceptually or empirically relevant to business-to-business or organisational settings.

Publications were excluded when they focused solely on technical system design without discussing organisational use, user behaviour, or implementation. Studies were also excluded when they addressed the circular economy only at a broad macro-policy level without attention to digital tools or organisational practice. Finally, studies focusing exclusively on consumer-side adoption were not central to the review, because this thesis focuses on organisational users in a business-to-business waste-value ecosystem.

Rather than applying a formal quality-scoring protocol, publications were assessed for their conceptual and empirical relevance to the research problem. The selected literature was organised into literature streams and concept-centric themes. These themes were compared across streams to identify recurring insights, conceptual tensions, limitations, and knowledge gaps relevant to the research problem. The resulting synthesis provides the basis for the literature-based analytical framework developed in the subsequent chapters.

2.3. Embedded single-case study design

The empirical part of the thesis follows an embedded single-case study design. Case-study research is appropriate when a contemporary phenomenon is investigated within its real-life context, particularly when the boundaries between the phenomenon and its context are not clearly evident (Yin, 2018). This applies to the use of information from digital circular-economy platforms. Such use cannot be understood independently from the organisational, technological, and ecosystem context in which it takes place.

In an embedded case design, one overarching case is examined through multiple units of analysis (Yin, 2018). In this study, the overarching case is the Milgro platform ecosystem. The embedded units of analysis are the individual client organisations using the platform. This design is appropriate because the research focuses on variation between organisations within one shared platform environment.

Client organisations have access to the same broader platform ecosystem, but may differ in how they use platform functionalities, how they interact with dashboards, how they rely on platform-related service channels, and how platform information is used in organisational practice. The embedded structure therefore makes it possible to compare organisations while keeping the broader platform provider and platform infrastructure constant. This strengthens internal comparison because observed differences in platform use can be analysed in relation to organisational and contextual conditions rather than differences in platform architecture or provider strategy.

The study does not aim for statistical generalisation to all digital circular-economy platforms. Instead, it aims for analytical generalisation: the development of theoretically informed insights that may be relevant to comparable socio-technical platform contexts (Flyvbjerg, 2006; Yin, 2018). The strength of the design lies in combining empirical depth within one platform ecosystem with systematic comparison across multiple client organisations.

2.4. Sequential explanatory mixed-methods design

The empirical study uses a sequential explanatory mixed-methods design. In this type of design, quantitative analysis is conducted first, followed by qualitative analysis that helps explain, contextualise, or elaborate the quantitative findings (Creswell & Plano Clark, 2017; Fetters et al., 2013). This design is suitable because the main research question requires both descriptive and explanatory analysis.

The quantitative phase provides breadth. It uses organisational-level platform data to map observable patterns of platform use across client organisations and to explore associations between dashboard information use and circular-performance indicators. This phase addresses the sub-questions concerned with variation in platform use and the relationship between dashboard information use and circular-performance indicators. The quantitative phase is exploratory and associative rather than causal.

The qualitative phase provides explanatory depth. Platform data can show whether and how organisations interact with the platform, but they cannot fully explain the organisational meaning of these patterns. Semi-structured interviews are therefore used to examine the socio-technical conditions identified in the analytical framework and to understand how these conditions may help explain the quantitative patterns.

The sequential structure is important. The quantitative phase first identifies patterns and contrasts. These patterns then inform the selection of organisations for the qualitative phase. The qualitative phase is therefore directly connected to the empirical patterns identified in the quantitative analysis. This strengthens the explanatory logic of the study, because interviews are not conducted independently of the platform data but are used to interpret and contextualise observed patterns.

The mixed-methods design is appropriate because neither phase can fully answer the main research question on its own. Quantitative data provide systematic insight into platform-engagement patterns across a broader set of organisations, but do not reveal the organisational meaning of those patterns. Qualitative data provide explanatory depth, but cannot by themselves map broader variation across the platform ecosystem. The integration of both phases makes it possible to connect observable platform engagement to the socio-technical conditions that may shape whether waste-related platform information becomes connected to organisational action for circular-performance improvement.

2.5. Case selection rationale

Milgro's digital circular-economy platform was selected as the empirical case because it fits the objective of this thesis. Milgro is a Dutch business-to-business service provider operating in a waste-value ecosystem. Its platform supports client organisations in managing waste-related processes, placing waste orders, monitoring waste and circular-performance information, and accessing operational, financial, environmental, and reporting-related information.

The case is methodologically relevant because the research examines how waste-related information within a digital circular-economy platform may become connected to organisational action for circular-performance improvement. This requires a case in which multiple types of waste-related information and platform interactions can be studied in relation to each other. Milgro's integrated

platform combines waste-order functionality with operational, financial, environmental, and reporting-related information. This provides an empirical setting in which platform information can be analysed in relation to organisational use, interpretation, and follow-up.

A further reason for selecting Milgro is the specific position of its platform within the European waste-value context. Milgro's patented platform is designed to provide an integrated view of waste-producing client organisations' waste flows and related performance information. It combines operational, financial, environmental, and reporting-related information within one digital environment. This distinguishes the case from more function-specific platform tools that mainly support CSRD reporting, waste administration, route planning, or logistics optimisation. For this thesis, this integrated character is analytically important because it allows the study to examine how different types of waste-related information may become connected to organisational action for circular-performance improvement.

Not all digital platforms in the waste-value chain provide the same empirical basis for this research objective. Platforms focused primarily on one specific function, such as waste administration, logistics optimisation, route planning, or CSRD compliance reporting, would provide a more limited basis for analysing how different types of waste-related information are used in relation to each other. Milgro's integrated platform provides a broader setting for examining how platform information is used by client organisations within a business-to-business waste-value ecosystem.

The case also provides access to a diverse set of client organisations using the same platform infrastructure. This makes it possible to compare patterns of platform use across organisations while keeping the broader platform environment constant. The Milgro case is therefore treated as an analytically relevant case that allows the research question to be examined in depth within a real-life platform ecosystem.

2.6. Empirical research flow

Figure 2.1 visualises the empirical research flow of the thesis. The research starts from the problem diagnosis and the literature review. The literature review leads to a literature-based analytical framework, which guides the empirical study. The framework is then translated into the Milgro case and used to structure the quantitative and qualitative phases.

The quantitative phase applies the framework to available platform and performance data. It maps variation in platform use across client organisations and explores associations between dashboard information use and circular-performance indicators. These results provide insight into empirical patterns, but do not explain by themselves why such patterns occur.

The quantitative findings then inform the purposive selection of organisations for the qualitative phase. Semi-structured interviews are used to examine the socio-technical conditions specified in the analytical framework and to interpret the quantitative patterns. The qualitative phase therefore provides explanatory depth for understanding the observed patterns.

The final synthesis integrates the quantitative and qualitative findings. This integration is used to answer the main research question and to refine the literature-based analytical framework. It also provides the basis for discussing the theoretical contribution, practical implications, limitations, and directions for future research.

Although the research process is presented sequentially for clarity, the design also contains iterative elements. Insights from the quantitative phase inform the qualitative sampling strategy, while qualitative findings are later used to interpret and refine the meaning of the quantitative patterns. The analytical framework also plays an iterative role: it guides the empirical analysis, while the empirical findings are used to refine the framework in the final synthesis.

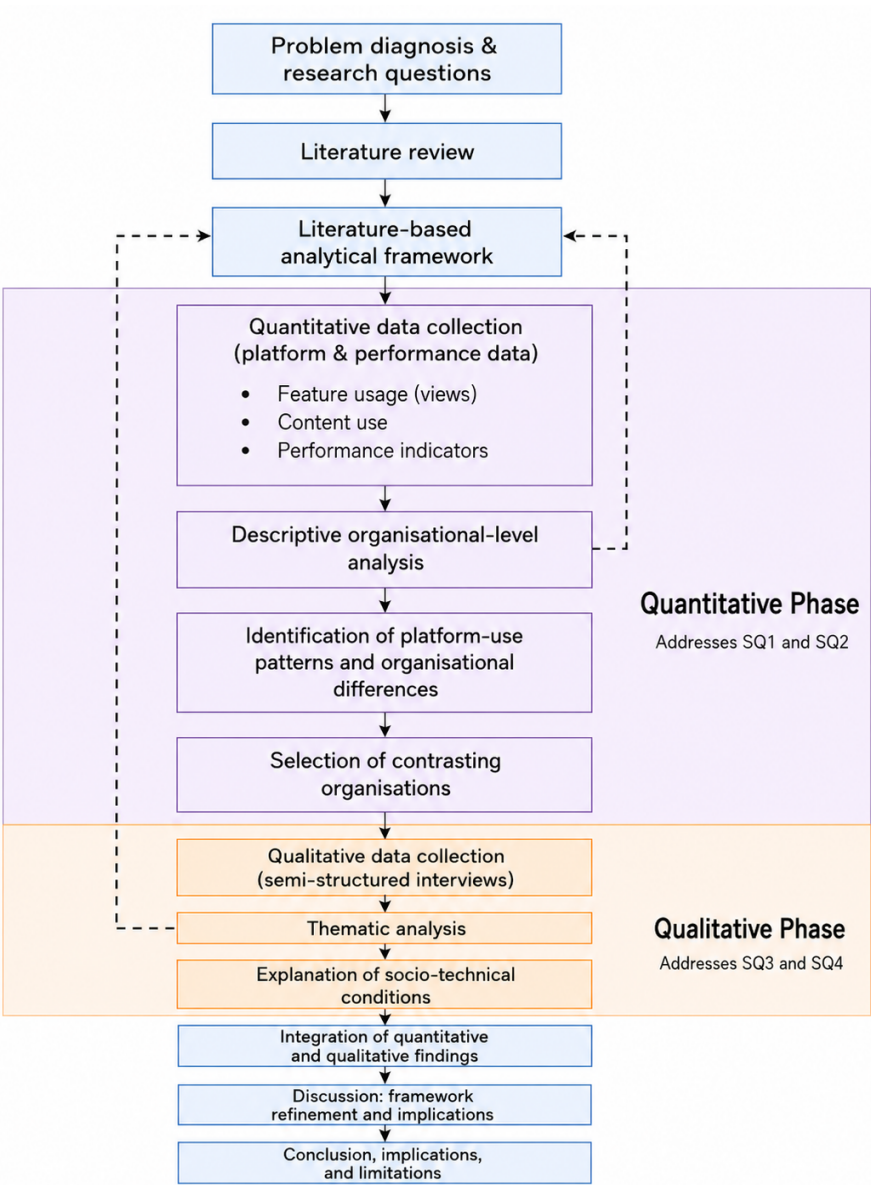


Figure 2.1: Empirical research flow of the sequential explanatory embedded single-case study design.

Figure 2.1 shows how the problem diagnosis and literature review lead to a literature-based analytical framework, which guides both empirical phases. The terminology in the figure is kept at the methodological level; the framework itself is developed in Chapter 4 and translated into the Milgro case in Chapters 5 and 6.

Table 2.1 summarises how the research sub-questions are aligned with the data sources, analytical methods, and analytical role of each phase. The table shows how the sequential explanatory design translates the research question into distinct but connected analytical steps.

Table 2.1: Alignment between sub-questions, data sources, analytical methods, and analytical role.

Sub-question	Data sources	Analytical methods	Analytical role
SQ1. Variation in platform use across organisations	Platform interaction data, order-channel data, support data, incident and damage/malfunction data, organisational context variables	Descriptive statistics, visualisation, non-parametric group comparisons	Mapping variation in multidimensional platform use across organisations and organisational contexts
SQ2. Dashboard use indicators and circular-performance indicators	Dashboard use indicators and circular-performance indicators	Spearman correlations, dashboard-intensity group comparisons, exploratory regression checks	Exploring indicative associations between dashboard use and circular-performance indicators
SQ3. User understanding and evaluation of dashboard information	Semi-structured interviews with selected organisations	Thematic analysis, combining deductive and inductive coding	Explaining how users understand, interpret, and evaluate platform information
SQ4. Organisational and ecosystem-level conditions shaping follow-up	Semi-structured interviews with selected organisations	Thematic analysis across framework-informed socio-technical conditions	Explaining which organisational and external conditions may facilitate or hinder the translation of platform information into organisational follow-up
Integration of quantitative and qualitative findings	Quantitative findings and qualitative interview findings	Integrated interpretation	Explaining how socio-technical conditions may shape whether platform information becomes connected to organisational action for circular-performance improvement

This alignment shows that each sub-question has a distinct analytical function. The final synthesis integrates the quantitative and qualitative evidence to answer the main research question and refine the literature-based analytical framework.

2.7. Validity, trustworthiness, and methodological limitations

Several measures were taken to strengthen the validity and trustworthiness of the research design. Construct validity is supported by the use of multiple sources of evidence, including platform interaction data, circular-performance indicators, organisational context variables, and interview data. This makes it possible to examine the research problem from different empirical perspectives and reduces the risk of interpreting platform behaviour in isolation.

Internal explanatory validity is supported by the sequential explanatory mixed-methods design. The quantitative phase identifies patterns and contrasts in platform use and circular-performance indicators. The qualitative phase then examines how these patterns can be understood in relation to the socio-technical conditions defined in the analytical framework. This sequencing reduces the risk of drawing explanatory conclusions from quantitative platform data alone.

Reliability is supported through transparent documentation of the research process. The quantitative data preparation and operationalisation are described in the quantitative data chapter. The qualitative sampling strategy, interview approach, and thematic analysis procedure are described in the qualitative research design chapter. Together, these descriptions make the analytical steps traceable and clarify how each empirical phase contributes to the research question.

Qualitative credibility is supported by using a semi-structured interview guide based on the analytical framework, while leaving room for respondents to introduce case-specific explanations. At the same time, interview data may be affected by recall bias, social desirability, or limited respondent knowledge

of all organisational practices. Comparing interview findings with platform data helps mitigate this risk by relating reported practices to observable platform-use patterns.

These measures strengthen the credibility of the study while also clarifying the scope of the claims that can be made. The embedded single-case design enables in-depth analysis within one platform ecosystem, but the findings should not be interpreted as statistically generalisable to all digital circular-economy platforms or waste-value ecosystems. The aim is therefore not statistical generalisation, but analytical generalisation: the development of theoretically informed insights that may be relevant to comparable socio-technical platform contexts.

Operational platform data also have limitations. They capture observable interactions with the platform, but not the organisational meaning of these interactions or the way waste-related information is interpreted and followed up in practice. The qualitative phase was therefore used to interpret these patterns. However, interview data remain dependent on respondents' knowledge, recall, and willingness to reflect on organisational practice.

The quantitative analysis is time-bounded and relies on available indicators as proxies for broader concepts. Platform-use indicators capture observable traces of interaction, while circular-performance indicators capture selected dimensions of circular performance. These limitations are addressed through triangulation, methodological sequencing, and a clear distinction between descriptive, associative, and explanatory claims. The final limitations and directions for future research are discussed in Chapter 10.

3 | Literature Review

This chapter reviews and synthesises literature relevant to the objective of this thesis: understanding under which socio-technical conditions information from a digital circular-economy platform may become connected to organisational action for circular-performance improvement. It brings together four literature streams that provide complementary insights into this problem: digital circular-economy platform literature, technology-adoption literature, socio-technical and practice-based information-systems literature, and digital-circularity literature. Sections 3.1 to 3.4 discuss these streams separately. Section 3.5 synthesises their insights and identifies the conceptual basis for the literature-based analytical framework developed in Chapter 4.

3.1. Digital circular-economy platforms

Digital platforms are increasingly discussed as potential enablers of the circular economy. They may support information visibility, coordination, and data exchange across value chains, thereby helping organisations to monitor material flows, identify inefficiencies, and coordinate circular activities (Carlos et al., 2024; Körppen et al., 2024). In waste-value ecosystems, such platforms are particularly relevant because circular value creation often depends on the ability to connect information from multiple actors, including waste producers, service providers, processors, and regulators.

Circular-economy platform literature shows that digital platforms can fulfil several roles. They may function as marketplaces for secondary materials, infrastructures for data sharing, coordination mechanisms for reverse logistics, or decision-support systems for circular performance management (Körppen et al., 2024; Petrik et al., 2025). Petrik et al. (2025) identify multiple platform mechanisms that support circular-economy success factors. This suggests that circular-economy platforms should not be understood merely as digital interfaces, but as systems that may support different forms of interaction within circular ecosystems.

This platform perspective reflects a broader shift from firm-centred circularity to ecosystem-based circularity. Circular value is rarely created by one organisation in isolation. Instead, it depends on the alignment of actors, data, incentives, and responsibilities across supply chains and waste-value networks (Blackburn et al., 2023; Körppen et al., 2024). Digital circular-economy platforms therefore operate in contexts where value creation is often distributed, data-dependent, and shaped by coordination across multiple actors (Blackburn et al., 2023; Petrik et al., 2025; Trevisan et al., 2023).

Empirical studies also suggest that digital platforms may support the execution of circular practices. For example, platform-enabled information exchange, stakeholder alignment, and decision-support mechanisms have been associated with improved waste-to-resource flows and environmental performance in industrial ecosystems (Hariyani et al., 2024; Li et al., 2025). Such findings support the view that digital circular-economy platforms may contribute to operational circularity not only by storing data, but also by supporting coordination and performance monitoring.

At the same time, the literature indicates that platform-enabled circular value creation is context-dependent. Platforms differ in governance arrangements, stakeholder roles, data ownership structures, and functional purposes (Petrik et al., 2025). These differences matter because the value of a platform does not follow automatically from its technical design. Circular value may also depend on whether organisations are able and willing to use the platform, whether data are reliable and interoperable, and whether platform information is connected to organisational decision-making processes (Körppen et al., 2024; Ndoka, 2023).

This literature stream provides two insights that are relevant for the analytical framework. First, digital circular-economy platforms can be understood as multifunctional systems rather than as single-purpose digital tools. They may support information use, transactions, coordination, decision support, and

ecosystem-level interaction. This suggests that platform use should be analysed as multidimensional rather than as one uniform form of use. Second, the literature indicates that platform value is shaped by ecosystem conditions, including data exchange, stakeholder roles, governance arrangements, and coordination across organisational boundaries.

However, this literature provides less insight into how organisational users interpret and use waste-related platform information in everyday practice, and how such information becomes connected to organisational follow-up for circular-performance improvement. This limitation makes it useful to complement platform literature with literature on user perceptions, organisational embedding, and digital-circularity barriers.

3.2. Technology acceptance and organisational technology use

Technology-adoption literature provides a second relevant perspective for this thesis. Classical adoption models explain technology use primarily through individual users' perceptions and behavioural intentions. The Technology Acceptance Model argues that perceived usefulness and perceived ease of use shape users' intentions to adopt a technology (Davis, 1989). The Unified Theory of Acceptance and Use of Technology extends this view by including factors such as social influence and facilitating conditions (Venkatesh et al., 2003).

These models were developed to explain individual technology acceptance. This means that they should not be used as a complete explanation of organisational platform adoption. In organisational contexts, the decision to adopt a platform may be shaped by management decisions, contracts, or service arrangements rather than by individual users alone. However, users still shape how the platform is enacted in practice, especially because digital circular-economy platforms often provide waste-related performance information rather than directly changing waste-producing practices. Users may decide whether to use platform functionalities for operational tasks, rely on alternative channels such as e-mail or telephone contact, consult dashboard information, or use this information for reporting, monitoring, or decision-making.

In this thesis, technology-adoption concepts are therefore used as micro-level concepts within a broader socio-technical framework. They help analyse how organisational users perceive, trust, interpret, and use platform functionalities and platform information. However, the translation from user-level acceptance or use to organisational action requires additional attention to routines, responsibilities, and ecosystem conditions. This is particularly relevant because technology use is shaped by the way users appropriate digital tools within specific work practices, rather than by initial acceptance alone (Carroll, 2004).

Technology-adoption literature also draws attention to trust and continued use. Users must not only accept a system initially, but also continue to perceive value during actual interaction with the technology (Bhattacharjee, 2001; Wu et al., 2024). In digital circular-economy platforms, trust is especially relevant because platform information often depends on data quality, categorisation, and input from multiple actors. If users doubt the reliability or relevance of the information, they may be less likely to use it as a basis for interpretation or follow-up.

Performance dashboards are relevant in this context because they can translate platform data into performance feedback and support monitoring, evaluation, and organisational learning (Barth & Formoso, 2008; Henri, 2006). However, dashboard information does not implement change by itself. Its practical relevance depends on whether users perceive the information as useful, understandable, and relevant to their organisational context.

The main insight from this literature stream is that user perceptions form an important micro-level condition for platform use. Concepts such as perceived usefulness, ease of use, trust, and continued use help explain why organisational users may or may not engage with platform functionalities and dashboard information. However, these concepts do not fully explain how information becomes connected to organisational action. For that, it is necessary to examine how platform information is embedded in routines, assigned to responsibilities, and shaped by wider ecosystem conditions.

3.3. Socio-technical and practice-based perspectives on information-systems use

Socio-technical and practice-based information-systems perspectives provide a third relevant literature stream for this thesis. These perspectives shift attention from technology acceptance as an individual decision to technology use as an organisational and situated practice. This is important because the research question concerns not only whether users access a digital platform, but also whether platform information becomes connected to organisational routines, responsibilities, and follow-up.

A socio-technical perspective assumes that digital technologies and social systems are mutually interdependent. Technologies may shape organisational possibilities, but their effects depend on how they are implemented, interpreted, and used by actors within specific contexts (Bostrom & Heinen, 1977; Orlikowski, 2000). The same digital platform may therefore lead to different forms of use across organisations, depending on routines, capabilities, role structures, managerial priorities, and external pressures.

Practice-based information-systems literature further emphasises that technology use is enacted in everyday work. Technologies do not have fixed organisational consequences. Their effects emerge through repeated use, interpretation, adaptation, and integration into practice (Orlikowski, 2000). From this perspective, platform use is not simply a matter of formal access or initial acceptance. It concerns how users make sense of platform information, how that information becomes part of work routines, and whether it becomes connected to decisions and possible action.

This perspective is relevant for digital circular-economy platforms because these platforms provide information that usually requires organisational interpretation. Dashboards may show waste volumes, separation rates, costs, or environmental indicators, but these figures do not automatically determine what an organisation should do. The organisational value of performance information depends not only on availability, but also on whether it is interpreted and used within decision-making routines (Moynihan & Lavertu, 2012; Moynihan & Pandey, 2010). Platform information may therefore remain primarily informational when it is not connected to organisational processes in which it can be discussed, interpreted, and potentially used.

Socio-technical and practice-based perspectives provide meso-level concepts for the analytical framework. They suggest that platform information becomes organisationally meaningful through situated interpretation and repeated use. They also indicate that organisational routines, roles, responsibilities, and decision-making practices may shape whether information becomes embedded in practice. At the same time, these perspectives do not fully account for the specific characteristics of digital circular-economy platforms. In particular, they provide less insight into ecosystem-level dependencies, data conditions, and inter-organisational coordination problems that may shape whether waste-related platform information can be acted upon across organisational boundaries. This limitation makes it necessary to include digital-circularity literature in the review.

3.4. Digital-circularity barriers at organisational and ecosystem levels

Where socio-technical literature explains how information systems become embedded in organisational practice, digital-circularity literature specifies barriers that are particularly relevant to circular-economy implementation. They are not limited to individual users or single organisations, but also arise within organisational structures, across ecosystem relationships, and in the broader institutional context. Trevisan et al. (2023) identify barriers across several dimensions, including knowledge management, governance, infrastructure, and regulation. This supports the view that digital circularity is a multi-level challenge.

At the micro level, barriers relate to users and their interaction with digital tools. These include limited digital skills, resistance to change, lack of perceived usefulness, limited trust in data, and insufficient time or capacity to engage with digital tools (Bennett & Müller Loose, 2024; Faiz et al., 2024). Such barriers may limit whether users consult dashboards, understand performance information, or consider platform information relevant for their work.

At the organisational level, barriers concern routines, capabilities, and responsibilities. Digital circular-economy platforms may provide relevant information, but organisations need internal processes, role allocation, managerial support, and digital capabilities to use that information in practice. When responsibilities are unclear, when routines are not aligned with platform use, or when digital tools are weakly connected to operational decision-making, platform information may remain disconnected from organisational follow-up.

At the ecosystem and institutional level, barriers relate to data conditions, inter-organisational coordination, and regulatory context. Digital circular-economy platforms often depend on data contributions, shared standards, and coordinated routines across multiple actors. Lack of data standards, inconsistent waste categorisation, weak supply-chain alignment, unclear data ownership, and dependence on external actors can limit the usefulness of platform information (Kovacic et al., 2020; Trevisan et al., 2023). Regulatory misalignment, infrastructure gaps, evolving reporting requirements, and limited implementation guidance may further complicate digital circularity (Charef & Lu, 2021; Trevisan et al., 2023).

Policy developments may increase pressure for traceability, reporting, and accountability, but they do not necessarily specify how digital circularity information should be embedded in organisational routines or operational improvement processes (Barteková & Börkey, 2022; European Commission, 2020; Ndoka, 2023). Organisations may therefore experience increasing pressure to report on circular performance while still facing uncertainty about how platform information should be used in operational practice.

Table 3.1: Multi-level digital-circularity barriers affecting the use of digital circular-economy platforms by organisational users.

Level	Examples of barriers	Illustrative sources
Micro level: users and interpretations	Limited digital skills, resistance to change, unclear perceived usefulness, lack of trust in data	Faiz et al. (2024); Bennett and Müller Loose (2024)
Meso level: organisational routines and responsibilities	Unclear internal responsibilities, weak managerial support, limited time or capacity, weak connection to operational decision-making	Orlikowski (2000); Besson and Rowe (2012); Trevisan et al. (2023)
Macro level: ecosystem and institutional conditions	Lack of data standards, inconsistent waste categorisation, dependence on external actors, regulatory misalignment, evolving reporting requirements	Kovacic et al. (2020); Charef and Lu (2021); Trevisan et al. (2023)

This literature stream contributes a multi-level perspective to the analytical framework. It indicates that digital circularity is shaped not only by user-level perceptions or technical access, but also by organisational routines, role allocation, data conditions, ecosystem coordination, and regulatory context. These barriers help explain why information from digital circular-economy platforms may remain disconnected from organisational follow-up, even when relevant data are available.

At the same time, the digital-circularity barriers literature has limitations for the purpose of this thesis. It identifies barriers across levels, but often provides less detailed explanation of how these barriers interact in the everyday organisational use of a specific digital circular-economy platform. In particular, limited empirical insight exists into how user perceptions, organisational routines, and ecosystem dependencies jointly shape the translation of platform information into organisational action for circular-performance improvement.

3.5. Literature synthesis

Across the reviewed literature, four insights are particularly relevant for this thesis. First, circular-economy platform literature shows that digital platforms may support information visibility, coordination, data exchange, and circular value creation. This literature often focuses on platform potential, governance, and design rather than everyday organisational use. It also indicates that platform use should be understood as multidimensional, because platforms can support different forms of interaction, such as information use, transactions, coordination, decision support, and ecosystem-level interaction.

Second, technology-adoption literature explains important user-level determinants of technology use, such as perceived usefulness, ease of use, trust, social influence, and facilitating conditions. These concepts are relevant for understanding how users perceive and evaluate digital platform information. However, these models primarily explain individual acceptance and use, and provide less insight into how platform information becomes connected to organisational routines or follow-up.

Third, socio-technical and practice-based information-systems literature explains that technology use is situated, routinised, and shaped by interactions between technological features and organisational practices. This literature is relevant because it suggests that platform information becomes meaningful through interpretation, repeated use, role structures, and organisational routines. However, it provides less specific insight into the particular characteristics of digital circular-economy platforms, where data and follow-up may depend on multiple actors across a waste-value ecosystem.

Fourth, digital-circularity literature identifies barriers across user, organisational, ecosystem, and institutional levels, including user capabilities, data quality, organisational routines, data standards, supply-chain coordination, and regulation. This literature shows that digital circularity is shaped by conditions beyond technical access. However, it provides less insight into how these barriers interact in the everyday use of a specific digital circular-economy platform and how they shape the translation from platform information to organisational action.

Table 3.2 summarises the established insights and remaining explanatory gaps across these literature streams.

Table 3.2: Literature synthesis across research streams, contrasting established insights with remaining explanatory gaps regarding information use and organisational action in digital circular-economy platform contexts.

Research area	Established insights	Remaining explanatory gaps
Digital circular-economy platforms	Digital platforms may enable information visibility, coordination, data exchange, transactions, decision support, and circular value creation across ecosystems. Platform use should be understood as multidimensional.	How are different platform functions used by organisations in everyday practice, and how do these uses relate to organisational follow-up?
Technology acceptance and organisational technology use	User perceptions, including usefulness, ease of use, trust, social influence, and facilitating conditions, shape individual technology use and continued engagement.	How do user-level perceptions influence the use of platform information when adoption is organisationally arranged and value creation is distributed across actors?
Socio-technical and practice-based information-systems perspectives	Technology use is situated, routinised, and shaped by interactions between technological features and organisational practices.	How does platform information become embedded in organisational routines, responsibilities, and decision-making processes?
Digital-circularity barriers	Barriers exist across user, organisational, ecosystem, and institutional levels, including capabilities, data quality, coordination, interoperability, and regulation.	How do these barriers interact in the use of a specific digital circular-economy platform, and how do they affect the translation of platform information into organisational action?

The synthesis indicates that digital circular-economy platforms should be analysed not only as technical infrastructures or business-model innovations, but also as socio-technical systems embedded in organisational and inter-organisational practice. The reviewed literature reveals three tensions that are particularly relevant for this thesis.

First, there is a tension between platform potential and organisational use. Circular-economy platform literature explains what platforms may enable, but provides less insight into how organisations use different platform functions in everyday practice. Second, there is a tension between individual acceptance and organisational action. Technology-adoption models explain how user perceptions shape technology use, but do not fully explain how platform information becomes embedded in organisational routines and responsibilities. Third, there is a tension between information availability

and action. Digital platforms may make waste flows and performance indicators visible, but visibility alone does not mean that organisations can interpret, embed, or act upon this information.

These tensions define the conceptual direction of this thesis. The focus shifts from digital platform adoption to multidimensional organisational platform use, and from information availability to organisational action. Platform literature supports the first shift by showing that platforms enable different forms of interaction. Technology-adoption literature provides micro-level concepts related to user perceptions, usefulness, ease of use, and trust. Socio-technical and practice-based perspectives provide meso-level concepts related to organisational embedding, routines, roles, responsibilities, and decision-making practices. Digital-circularity literature adds macro-level concepts related to data conditions, ecosystem dependencies, inter-organisational coordination, and regulatory context.

The research gap addressed in this thesis is therefore explanatory in nature. Existing literature provides fragmented insights into platform potential, user acceptance, organisational embedding, and digital-circularity barriers, but does not sufficiently explain how waste-related platform information becomes connected to organisational action in business-to-business waste-value ecosystems. This is particularly relevant in a circular waste-management context, where platform information concerns residual material flows and where circular follow-up may depend on actors and infrastructures across the wider waste-value ecosystem.

Together, these insights provide the conceptual basis for the literature-based analytical framework developed in Chapter 4. The framework distinguishes between observable dimensions of platform use and the socio-technical conditions that may shape whether waste-related platform information supports organisational action for circular-performance improvement. It therefore functions as the analytical lens for the empirical study of the Milgro platform ecosystem.

4 | Literature-based Analytical Framework

Chapter 3 synthesised four literature streams and identified an explanatory research gap concerning how waste-related platform information becomes connected to organisational action in business-to-business waste-value ecosystems. This chapter translates that synthesis into a literature-based analytical framework for the empirical study.

The framework is not intended as a causal model. Rather, it identifies two elements that guide the empirical analysis: the observable dimensions of platform use and the socio-technical conditions that may shape whether waste-related platform information becomes connected to organisational action for circular-performance improvement.

The chapter is structured as follows. Section 4.1 explains how the literature synthesis is translated into the analytical framework. Section 4.2 discusses the multidimensional understanding of platform use. Section 4.3 presents the multi-level socio-technical conditions included in the framework. Section 4.4 summarises the framework and explains how it guides the empirical study.

4.1. From literature synthesis to analytical framework

The literature synthesis in Chapter 3 shows that the research problem cannot be explained by one literature stream alone. Digital circular-economy platform literature indicates that platforms may support several forms of interaction, but provides less insight into how organisations use platform information in everyday practice. Technology-adoption literature explains why individual users may accept or continue using a technology, but provides limited insight into organisational follow-up. Socio-technical and practice-based perspectives address organisational embedding, but are less specific to digital circular-economy platforms. Digital-circularity literature identifies barriers across levels, but does not fully explain how these barriers interact in the use of a specific platform.

For this reason, the analytical framework integrates selected concepts from these streams. The selected concepts are not intended to represent all concepts discussed in the reviewed literature. They are included because they are directly relevant to the main research question: *Under which socio-technical conditions can information within a digital circular-economy platform support organisational action for circular-performance improvement in a business-to-business waste-value ecosystem?*

The framework consists of two components. First, it treats platform use as multidimensional. This reflects the insight that digital circular-economy platforms are not single-purpose tools, but may support different forms of interaction. Second, it treats the translation of platform information into organisational action as a multi-level socio-technical issue. This reflects the insight that information use may be shaped by user-level, organisational, and ecosystem-level conditions.

The framework remains conceptual at this stage of the thesis. It specifies the analytical categories used to guide the empirical study, but it does not yet define the case-specific indicators used in the Milgro analysis. The empirical translation of the framework into the Milgro case is discussed in Chapter 5, while the detailed quantitative operationalisation is presented in Chapter 6.

4.2. Multidimensional platform use

The first component of the analytical framework is a multidimensional understanding of platform use. This follows from digital circular-economy platform literature, which suggests that platforms may support multiple functions within circular ecosystems. These functions may include information access, performance monitoring, transactions, coordination, decision support, and ecosystem-level interaction.

This multidimensional perspective is important because platform use should not be reduced to one general usage measure. An organisation may use a platform for routine operational interactions without using it intensively for performance monitoring. Another organisation may consult information dashboards but rely on other channels for coordination or support. Treating platform use as multidimensional therefore makes it possible to distinguish between different forms of interaction with a digital circular-economy platform.

In this thesis, the multidimensional component functions as a conceptual starting point. It sensitises the empirical analysis to the possibility that organisations may use different parts of a platform in different ways. The specific forms of platform use that can be observed within the Milgro case depend on the available platform data and the functionalities of the platform. These case-specific dimensions are introduced in the empirical case study and operationalisation chapters.

4.3. Multi-level socio-technical conditions

The second component of the framework is a multi-level understanding of socio-technical conditions. The literature review suggests that the use of platform information cannot be explained by technical access or individual acceptance alone. Instead, platform information may become relevant for organisational action only within a broader socio-technical context.

At the micro level, the framework draws mainly on technology-adoption literature. Although these concepts were originally developed to explain individual technology acceptance and use, they remain relevant in this thesis because organisational platform use is enacted through individual users. These users access, interpret, and evaluate platform information on behalf of the organisation. Concepts such as perceived usefulness, relevance, trust, and user interpretation therefore help explain whether platform information is consulted and considered meaningful. However, they do not explain by themselves whether this information becomes embedded in organisational routines or connected to organisational action.

At the meso level, the framework draws on socio-technical and practice-based information-systems literature. This level focuses on organisational routines, role structures, responsibilities, decision-making practices, and organisational embedding. These conditions matter because platform information may need to become part of organisational practice before it can support follow-up.

At the macro level, the framework draws mainly on digital-circularity literature. This level concerns data conditions, ecosystem dependencies, inter-organisational coordination, and regulatory context. These conditions are relevant because digital circular-economy platforms operate in waste-value ecosystems where data quality, interpretation, and possible follow-up often depend on actors beyond a single organisation.

The three levels are analytically distinct, but they should not be understood as isolated. User perceptions may be shaped by organisational routines. Organisational routines may be influenced by ecosystem dependencies. Ecosystem conditions may affect the reliability or practical relevance of platform information. The framework therefore treats socio-technical conditions as interrelated analytical categories rather than as separate causal factors.

4.4. Analytical framework guiding the empirical study

Table 4.1 summarises the literature-based analytical framework. It shows how the reviewed literature streams are translated into framework components and selected analytical concepts.

Table 4.1: Literature-based analytical framework.

Literature stream	Framework component	Selected analytical concepts
Digital circular-economy platform literature	Multidimensional platform use	Information use; transactions; coordination; decision support; ecosystem-level interaction
Technology-adoption literature	Micro-level user conditions	Perceived usefulness; relevance; trust; user interpretation
Socio-technical and practice-based information-systems literature	Meso-level organisational conditions	Organisational routines; role structures; responsibilities; decision-making practices; organisational embedding
Digital-circularity literature	Macro-level ecosystem and institutional conditions	Data conditions; ecosystem dependencies; inter-organisational coordination; regulatory context

Figure 4.1 visualises how the literature streams reviewed in Chapter 3 are translated into the literature-based analytical framework. The arrows indicate analytical translation from literature streams into framework components.

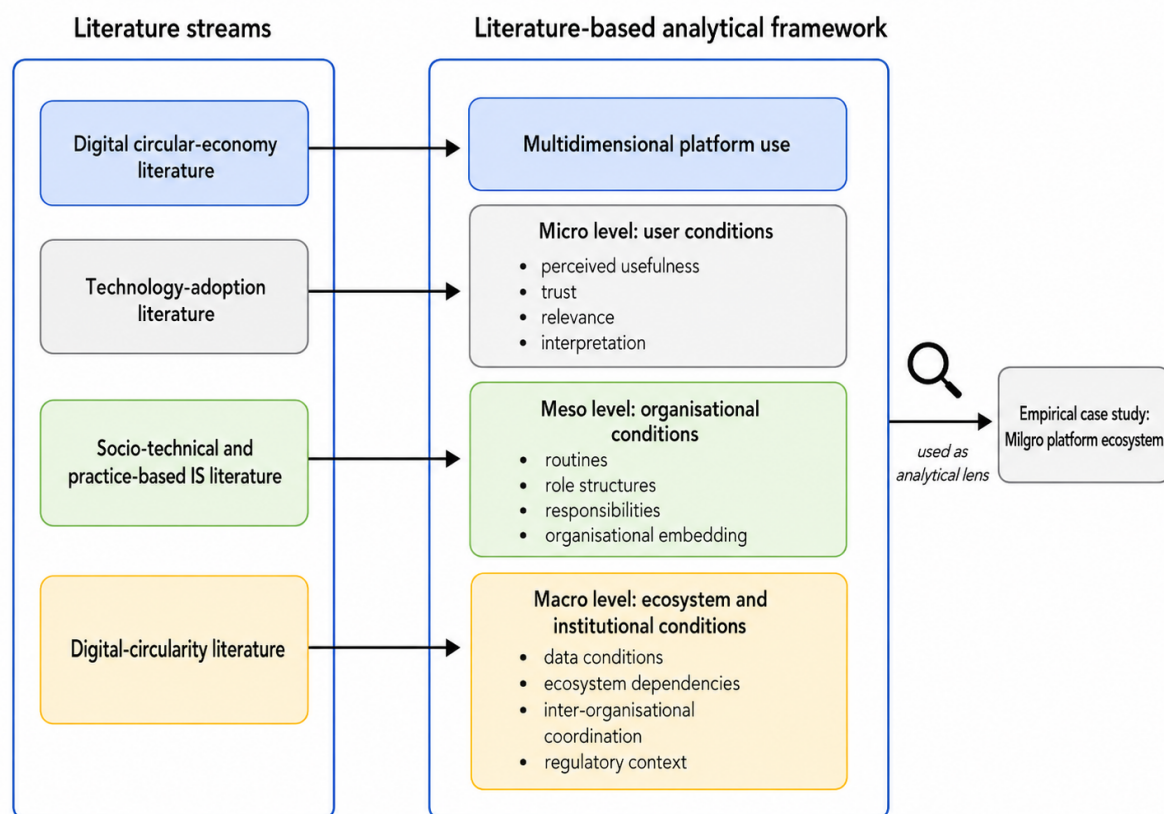


Figure 4.1: Literature-based analytical framework used as analytical lens for the empirical case study.

The multidimensional platform-use component is treated as an analytical starting point for observing platform interaction. The micro-, meso-, and macro-level conditions are treated as socio-technical

conditions that may shape whether platform information becomes connected to organisational follow-up.

The framework guides the empirical study in two ways. First, the multidimensional component guides the analysis of how organisations use a digital circular-economy platform. Second, the multi-level component guides the analysis of the socio-technical conditions that may shape whether platform information becomes connected to organisational action. The framework is therefore used as an analytical lens rather than as a causal model. It does not assume that any single condition directly produces circular-performance improvement, nor does it specify in advance which conditions will be most important in the empirical case.

The next chapter translates this literature-based framework into the empirical case study. It introduces Milgro's platform ecosystem, the relevant actors, and the case-specific forms of platform use that can be analysed with the available data.

5 | Empirical Case Study: Milgro

Chapter 4 developed a literature-based analytical framework for analysing how information from a digital circular-economy platform may become connected to organisational action for circular-performance improvement. The framework treats platform use as multidimensional and examines socio-technical conditions at user, organisational, and ecosystem levels.

This chapter translates that framework into the empirical case study of Milgro's platform ecosystem. It introduces the case context, the relevant actors, the main types of platform interaction, and the case-specific translation of multidimensional platform use. The chapter therefore forms the bridge between the conceptual framework developed in Chapter 4 and the quantitative operationalisation presented in Chapter 6.

The chapter is structured as follows. Section 5.1 explains how the analytical framework is translated into the empirical case. Section 5.2 introduces Milgro's digital circular-economy platform. Section 5.3 describes the platform ecosystem and its main actors. Section 5.4 discusses platform roles and user interactions. Section 5.5 explains how multidimensional platform use is translated into case-specific empirical dimensions. Section 5.6 links the case study to the subsequent quantitative and qualitative phases.

5.1. From analytical framework to empirical case study

The literature-based analytical framework developed in Chapter 4 remains conceptual. It identifies broad dimensions of platform use and socio-technical conditions that may be relevant for understanding how platform information becomes connected to organisational action. To study these concepts empirically, the framework must be translated into the specific platform context of Milgro.

This translation involves two steps. First, the multidimensional component of the framework is related to the forms of platform interaction that can be observed within the Milgro platform ecosystem. Second, the multi-level component of the framework is used to structure the empirical analysis of user, organisational, and ecosystem-level conditions. The first step is mainly relevant for the quantitative phase, where platform-use patterns are analysed through available platform data. The second step is mainly relevant for the qualitative phase, where interviews are used to examine the socio-technical conditions specified in the framework.

This chapter does not present the detailed data preparation or statistical operationalisation. These are discussed in Chapter 6. Instead, the purpose of this chapter is to clarify the empirical setting in which the analytical framework is applied.

5.2. Case context: Milgro's digital circular-economy platform

The empirical case selected for this thesis is Milgro's digital circular-economy platform. Milgro's platform is designed around the position of the waste-producing client organisation. The platform does not merely register waste transactions. It provides client organisations with an integrated view of their waste streams, separation performance, waste-related costs, and environmental indicators, including CO₂-related impacts. In this way, the platform supports monitoring, reporting, and decision-making about waste and circular performance.

The chain-wide character of the platform should be understood from the perspective of the client organisation's waste flows. Milgro brings together information related to waste generation, collection, processing, and potential revalorisation within one digital environment. Where possible, the platform and related service infrastructure help connect client organisations' waste streams to processing routes in which waste can be treated as a resource.

The Milgro case is analytically relevant because of the integrated character of the platform and the

presence of multiple client organisations within the same platform ecosystem. This makes it possible to study variation in platform use while keeping the broader platform infrastructure and provider context constant.

The platform does not only provide retrospective waste information. It also supports operational interaction between client organisations and Milgro's waste-management services. This makes the case relevant for analysing both information use and operational platform interaction. The platform context therefore reflects the broader issue addressed in this thesis: digital circular-economy platforms may provide information visibility, but their contribution to circular-performance improvement depends on how organisations use and act upon that information.

The Milgro case is not treated as statistically representative of all digital circular-economy platforms. It is treated as an analytically relevant case that allows the research question to be examined in depth within a real-life platform ecosystem.

5.3. Platform ecosystem and actors

The Milgro platform ecosystem involves several types of actors. Milgro acts as the platform and service provider. It combines waste-management services with digital data and reporting functionalities. Through the platform, Milgro provides client organisations with access to waste-related operational and performance information.

Client organisations are the waste-producing organisations connected to the platform. They use the platform to manage waste-related processes, monitor information, and interact with Milgro or related service channels. These organisations differ in sector, size, operational complexity, and internal responsibilities for waste management and sustainability reporting. These differences are relevant because they may shape how platform information is used in practice.

Other actors in the wider waste-value ecosystem may include waste collectors, processors, suppliers, customers, and regulatory bodies. These actors are not all direct users of the platform, but they can influence the context in which waste-related information is generated, classified, processed, and used. For example, waste categorisation, reporting expectations, and processing options may depend on actors beyond the client organisation itself.

This ecosystem setting is important for the empirical study. It means that platform information is not produced or used in isolation. It is embedded in a wider network of waste-related practices, data flows, service relationships, and regulatory expectations. This makes the Milgro case suitable for studying platform information as part of a socio-technical and multi-actor system.

5.4. Platform roles and user interactions

Within client organisations, platform use may involve different types of users. Operational users are mainly concerned with day-to-day waste-management activities. Their tasks may include placing waste orders, reporting incidents, requesting support, or resolving practical issues related to containers, waste flows, or collection processes.

Strategic or managerial users may use aggregated platform information for monitoring, reporting, target-setting, sustainability communication, or identifying possible improvement opportunities. In practice, these roles may overlap. In smaller organisations, one person may be responsible for both operational coordination and reporting. In larger organisations, waste management, sustainability, procurement, facility management, and reporting may be distributed across several roles or departments.

The Milgro platform supports several forms of interaction. Organisations may use digital channels for recurring operational processes, consult dashboards to access performance information, contact support through service channels, or report non-routine operational issues. These forms of interaction are not analytically equivalent. They may reflect different purposes, routines, and organisational needs.

This distinction matters for the empirical analysis because the thesis does not assume that all organisations use the platform in the same way or for the same purpose. One organisation may use the platform mainly for operational transactions, while another may use dashboard information more

actively for monitoring or reporting. A differentiated understanding of platform interaction is therefore needed to analyse variation across client organisations.

5.5. Case-specific translation of multidimensional platform use

Chapter 4 established that platform use should be treated as multidimensional. Within the Milgro case, this conceptual insight is translated into four empirical dimensions of organisational platform engagement. These dimensions are case-specific. They reflect the types of platform interaction that can be observed within the available Milgro data and platform context.

First, informational dashboard engagement refers to the use of dashboards and related platform functionalities that provide insight into waste flows, costs, environmental indicators, and circular performance. This dimension is relevant because dashboards translate platform data into performance information that may support monitoring and evaluation.

Second, routine transactional engagement refers to the use of standardised digital channels for recurring operational interactions, such as routine waste orders. This dimension captures whether recurring waste-related processes are organised through digital platform channels or through alternative routes.

Third, support-related engagement refers to interactions with Milgro or related service channels to resolve questions, uncertainties, or operational issues. These interactions may indicate assistance needs, coordination requirements, or active use of the platform and its surrounding service infrastructure.

Fourth, non-routine operational engagement refers to exceptional or irregular interactions, such as incidental orders, damage reports, or malfunction-related requests. These interactions capture how organisations deal with operational variation and unexpected situations within the waste-management process.

Distinguishing these dimensions prevents platform use from being reduced to a single intensity measure. High dashboard activity does not necessarily imply that routine transactions are digitised. Frequent support contact does not necessarily mean that dashboard information is used for circular-performance improvement. Conversely, low dashboard activity does not automatically imply that an organisation is disengaged from the platform as a whole. The four dimensions therefore provide a differentiated empirical basis for analysing how organisations use the Milgro platform.

Figure 5.1 summarises how the literature-based analytical framework is translated into the Milgro case. It distinguishes between socio-technical conditions, case-specific dimensions of platform engagement, and circular-performance indicators. The arrows indicate the analytical role of each component within the empirical research design and should not be interpreted as causal relationships.

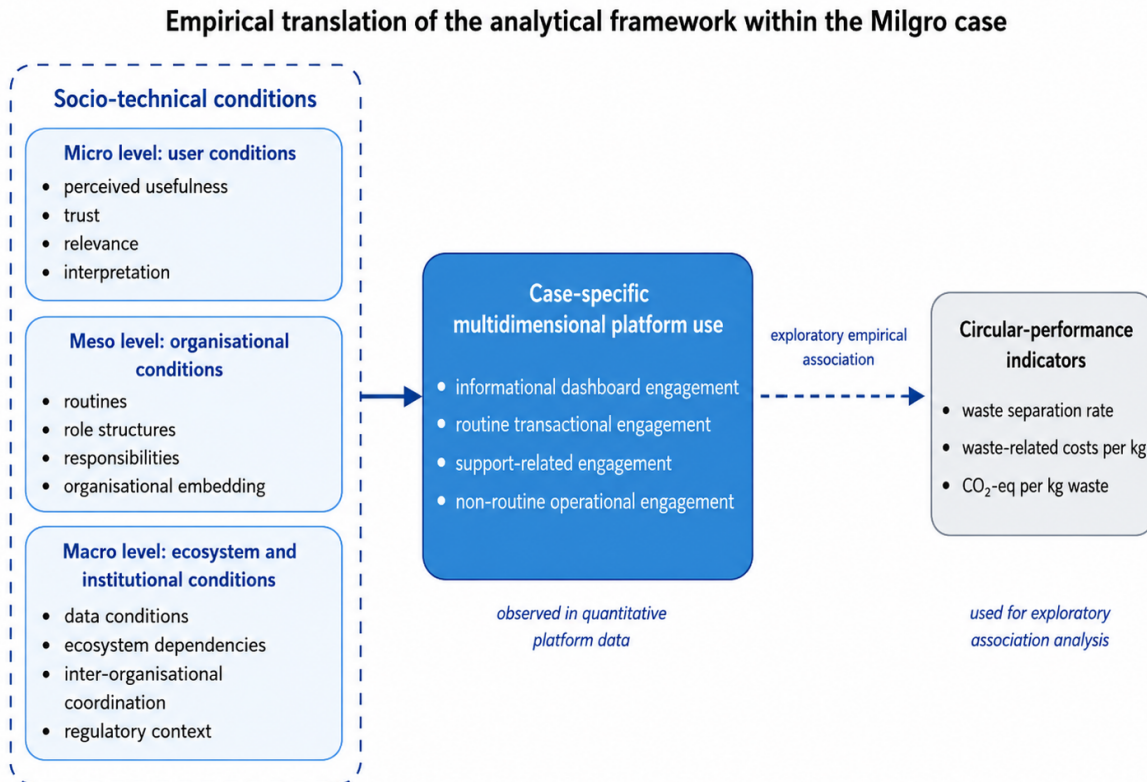


Figure 5.1: Empirical translation of the analytical framework within the Milgro case.

The figure shows how the literature-based framework is translated into socio-technical conditions, case-specific platform-engagement dimensions, and circular-performance indicators for the empirical analysis of the Milgro case. The detailed operationalisation of the four engagement dimensions is presented in Chapter 6. The socio-technical conditions are examined through the qualitative research design and findings in Chapters 8 and 9.

5.6. Link to the quantitative and qualitative phases

The case-specific translation developed in this chapter informs both empirical phases of the thesis. In the quantitative phase, the four dimensions of platform engagement provide the basis for constructing observable indicators from Milgro's platform data. These indicators are used to examine variation in platform use across client organisations and to explore whether different forms of platform use move together. The quantitative phase also examines whether informational dashboard engagement is associated with circular-performance indicators, such as waste separation, waste-related costs, and CO₂-related impact.

The qualitative phase is used to explain and contextualise the patterns identified in the quantitative analysis. Semi-structured interviews with selected client organisations examine how users understand dashboard information, which barriers and enabling conditions they encounter, and how platform information becomes connected, or fails to become connected, to organisational follow-up.

The integration of both phases is developed in Chapter 10. There, the literature-based analytical framework is refined on the basis of the empirical findings. This refinement specifies the socio-technical conditions under which platform information may move beyond visibility and become connected to organisational action for circular-performance improvement.

6 | Quantitative Data and Operationalisation

Chapter 5 translated the literature-based analytical framework into the empirical context of the Milgro platform ecosystem. It introduced the case-specific forms of platform interaction that are relevant for the quantitative analysis. This chapter explains how these forms of interaction are operationalised using the available Milgro data.

The quantitative phase has two analytical purposes. First, it maps variation in platform use across client organisations. Second, it explores whether informational dashboard engagement is associated with available circular-performance indicators. The analysis is descriptive, comparative, and exploratory. It does not aim to establish causal effects between platform use and circular-performance improvement.

In this chapter, the term *organisational platform engagement* is used as an empirical operationalisation of multidimensional platform use. It refers to the observable ways in which client organisations interact with the Milgro platform and its related service channels. This includes dashboard activity, routine digital transactions, support interactions, and non-routine operational interactions. The term is therefore used in a data-oriented sense. It does not imply that observable platform interaction by itself captures whether platform information is interpreted, embedded in routines, or translated into organisational action. These interpretive and organisational aspects are examined in the qualitative phase.

The raw data used in this chapter were originally generated for operational and administrative purposes rather than for academic research. As a result, the source files differed in structure, naming conventions, temporal coverage, identifiers, and level of aggregation. Data preparation is therefore treated as part of the research methodology. It shapes how organisational platform behaviour is represented in the final analytical dataset.

This chapter reports the methodological logic and key analytical choices underlying the data preparation process. More detailed dataset-specific procedures are documented in the appendices. Appendix A reports the dataset-specific cleaning steps, feature-table construction, source-level dataset sizes, and completeness checks. Appendix B documents the support-data matching hierarchy and match distribution. Appendix C documents the preparation and matching of incident and damage/malfunction records.

This chapter is structured as follows. Section 6.1 explains the purpose of the quantitative phase. Section 6.2 describes the quantitative data sources. Section 6.3 explains the data preparation and construction of the analytical dataset. Section 6.4 operationalises multidimensional platform engagement. Section 6.5 operationalises the circular-performance indicators. Section 6.6 describes the quantitative analytical methods. Section 6.7 discusses implications for interpretation and links the chapter to the quantitative results.

6.1. Purpose of the quantitative phase

The quantitative phase addresses the first two empirical sub-questions of this thesis. It examines observable platform-engagement patterns across client organisations and explores whether dashboard-information use is associated with available circular-performance indicators. In doing so, the quantitative phase provides empirical breadth, as it enables systematic comparison across 196 client organisations within the same Milgro platform ecosystem.

The quantitative phase is designed to examine two empirical issues. First, it analyses whether different platform functionalities are used together or whether they vary independently across client organisations. This is important because intensive use of one functionality, such as dashboard viewing,

does not necessarily imply intensive use of other platform functionalities, such as digital waste-order channels, support interactions, or non-routine operational channels.

Second, the quantitative phase explores whether dashboard-information use is associated with circular-performance indicators. This analysis focuses specifically on informational dashboard engagement, because dashboards are the main interface through which client organisations access waste-performance information. The underlying expectation is that, if dashboard information supports monitoring and improvement, organisations that use dashboard information more intensively or more consistently may be associated with better circular-performance outcomes. These outcomes are measured through available indicators, including waste separation, waste-related costs, and CO₂-equivalent emissions per kilogram of waste. The analysis is exploratory and associative rather than causal.

The quantitative phase therefore provides the empirical basis for the qualitative phase. By identifying variation in platform use and indicative associations between dashboard engagement and performance indicators, it helps determine which patterns require further explanation. The subsequent interviews are used to interpret the organisational meaning behind these patterns and to examine the socio-technical conditions under which platform information becomes connected to organisational follow-up.

6.2. Quantitative data sources

The quantitative analysis combines several internal datasets provided by Milgro. These datasets capture platform interaction, operational ordering, support activity, non-routine operational events, customer characteristics, and circular-performance indicators. Together, they provide the empirical basis for analysing multidimensional platform engagement and its relationship with circular-performance indicators.

Customer characteristics provide contextual information about client organisations. These variables include company identifiers, sector classifications, country codes, and location-related descriptors. They are used to describe the organisational context and to support comparisons between groups where analytically relevant.

Standard-order data capture how routine waste orders are registered and processed across different order routes and systems. These data distinguish between orders placed through digital platform channels and orders processed through other internal or external routes. They are used to operationalise routine transactional engagement.

Total-order data provide the denominator used to normalise platform interactions. This is necessary because client organisations differ substantially in operational scale. Organisations with more waste activity naturally generate more orders, support interactions, and operational events. Normalising interaction counts relative to order volume makes it possible to compare engagement intensity across organisations of different sizes.

Dashboard data capture dashboard views and dashboard activity over time. These data are used to operationalise informational dashboard engagement. They provide insight into whether and how frequently client organisations access dashboard-based performance information.

Support data capture interactions between client organisations and Milgro through support or service channels. These interactions may occur through channels such as e-mail, telephone, portal, or chat, depending on the available records. Support data are used to operationalise support-related engagement.

Incident and damage/malfunction data capture non-routine operational interactions. These include incidental orders and records related to damage, malfunction, or other exceptional operational situations. These data are used to operationalise non-routine operational engagement.

Circular-performance indicators are provided through Milgro's scores data. These data include waste separation percentage, waste-related costs per kilogram, and CO₂-equivalent emissions per kilogram of waste. They are used to examine whether informational dashboard engagement is associated with observable differences in circular-performance indicators.

Reference data are used as supporting reference data for validation and matching. These data help restrict and validate records for relevant entities where needed, particularly in relation to support and non-routine operational records.

Table 6.1: Quantitative data sources and analytical role

Data source	Main content	Analytical role
Customer characteristics	Sector, country, location-related descriptors, client identifiers	Organisational context and group comparisons
Standard-order data	Routine orders and order routes	Routine transactional engagement
Total-order data	Total order volume	Denominator for normalisation
Dashboard data	Dashboard views and dashboard activity	Informational dashboard engagement
Support data	Support interactions and support channels	Support-related engagement
Incident and damage/malfunction data	Incidental orders and damage or malfunction events	Non-routine operational engagement
Scores data	Waste separation percentage, costs per kilogram, CO ₂ -equivalent emissions per kilogram	Circular-performance indicators
Waste-producer reference data	Reference identifiers for relevant entities	Validation and restriction of selected records

6.3. Data preparation and construction of the analytical dataset

The quantitative data preparation consisted of transforming raw operational records into an integrated analytical dataset suitable for organisational-level and company-quarter-level analysis. The preparation process included cleaning, harmonisation, matching, aggregation, merging, normalisation, missing-value handling, and feature construction.

6.3.1. Preprocessing workflow

The preprocessing workflow can be summarised in five main stages. First, each raw source file was imported and cleaned separately. Column names were harmonised, time variables were parsed, numeric fields were converted to consistent formats, and irrelevant or invalid records were removed. Second, company and branch identifiers were standardised and matched across datasets. Third, a cross-dataset consistency check was used to identify entities that appeared in only one source dataset and required review before inclusion. Fourth, company-quarter feature tables were constructed for the main behavioural domains. Finally, these feature tables were merged into the final analytical dataset.

Figure 6.1 summarises the preprocessing pipeline from raw operational data to the final analytical dataset. The figure shows the main methodological steps used to transform Milgro's operational records into a harmonised company-quarter dataset. Dataset-specific cleaning steps, feature-table construction, source-level dataset sizes, and completeness checks are documented in Appendix A. The support-data matching hierarchy is documented in Appendix B, while the preparation and matching of incident and damage/malfunction records are documented in Appendix C.

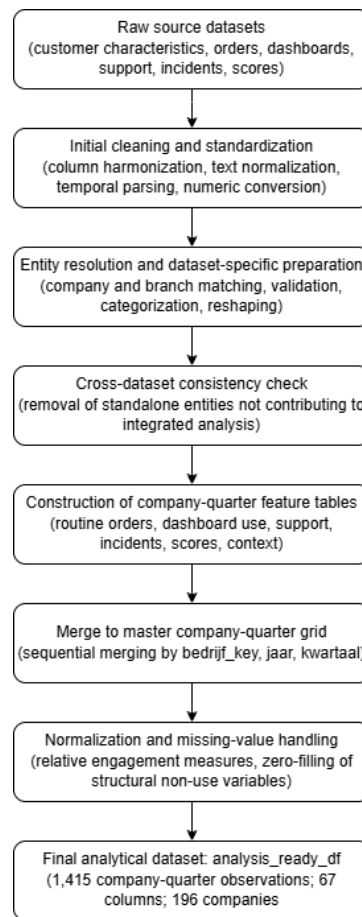


Figure 6.1: Preprocessing pipeline from raw operational data to the final analytical dataset.

Figure 6.1 summarises the main steps used to transform Milgro’s raw operational records into a harmonised company-quarter dataset for quantitative analysis.

This preprocessing was necessary because the operational records were not originally collected for research purposes. The workflow aimed to ensure that observed differences between organisations reflected substantively meaningful variation in platform engagement rather than inconsistencies in naming conventions, temporal coverage, source-system structure, or duplicate organisational representations.

All datasets were restricted to a common analytical window from 2024Q1 to 2025Q4. Observations from 2023 were excluded because the period before 2024 was considered less reliable for integrated comparison across source systems, partly due to a system transition around mid-2023. Restricting the analysis to 2024Q1 onward improved internal consistency and reduced the risk that observed differences reflected transitional system effects rather than substantive variation in platform use.

6.3.2. Entity harmonisation and matching

A central challenge in constructing the analytical dataset was that company and branch identifiers were not fully consistent across source systems. Because the analysis compares organisations across multiple behavioural domains, a shared company-level identifier was required.

Entity harmonisation followed general principles of record linkage and entity resolution (Christen, 2012). It combined text normalisation, deterministic matching, semi-deterministic matching, and manual validation for unresolved but analytically relevant cases. Company and branch names were standardised by removing formatting inconsistencies, harmonising punctuation and spacing, converting text to lowercase, and reducing variation in common company-name elements. These standardised strings were then used to construct company-level and branch-level match keys.

The support and incident and damage/malfunction datasets required the most extensive matching procedures because their records did not always align directly with the cleaned customer reference data. For these datasets, hierarchical matching was applied. Records were first matched using the most precise available identifiers or branch-level names. Remaining unmatched records were then matched using company-level names and auxiliary datasets, including total-order and standard-order data. Residual cases were manually reviewed when they were analytically relevant and could be assigned reliably.

Manual validation was applied conservatively. Records were only assigned to a company when the available identifiers, standardised names, or auxiliary information provided sufficient confidence in the match. Ambiguous records were not forced into the dataset, because an incorrect match would be more problematic for cross-organisational comparison than a limited loss of records. This approach prioritised the validity of organisational comparison over maximising the number of matched observations. Because these records required the most extensive matching procedures, the detailed matching hierarchies and match distributions are reported separately. Appendix B documents the support-data matching procedure, including the hierarchical matching steps, final match distribution, and flowchart shown in Figure B.1. Appendix C documents the corresponding procedure for incident and damage/malfunction records.

6.3.3. Aggregation to the company-quarter level

After dataset-specific cleaning and matching, each source dataset was aggregated to the company-quarter level where temporal comparison was required. This level of aggregation was selected because it provides a balance between temporal detail and organisational comparability. It allows variation over time to be retained while avoiding excessive noise at the individual interaction level.

The company-quarter level also aligns with the objective of the quantitative phase. The analysis is concerned with comparing organisational engagement patterns, not with interpreting individual dashboard views, support interactions, or operational events in isolation.

Separate feature tables were constructed for the main analytical domains: routine order channel use, dashboard activity and dashboard views, support interactions, incident and damage/malfunction interactions, circular-performance scores, total order volume, and organisational context variables. These feature tables were merged through a master company-quarter grid, defined as the union of observed company-quarter combinations across the main engagement and performance datasets. The final merge was conducted using company key, year, and quarter. Contextual variables, such as sector and country code, were merged at the company level.

This procedure produced an integrated company-quarter dataset in which different forms of engagement could be compared across organisations and linked to circular-performance indicators where available.

6.3.4. Normalisation and missing-value handling

A key methodological decision was to operationalise engagement primarily through relative rather than absolute measures. Organisations differ substantially in operational scale. Larger organisations naturally generate more orders, dashboard views, support interactions, and incident records. Raw counts would therefore reflect organisational size as well as behavioural intensity.

To improve comparability, several count-based variables were normalised by total order volume and expressed per 100 orders. This applies to dashboard views, support interactions, incidental orders, and damage or malfunction events. Channel-based variables were expressed as proportions of their corresponding totals. This makes it possible to compare not only how intensively organisations engage, but also how their engagement is distributed across channels and interaction types.

Customer size was used as a complementary contextual grouping variable. It was derived from average total order volume over the observation period. Organisations were ranked by average total order volume and divided into three equally sized tertiles, labelled small, medium-sized, and large. Customer size should therefore be interpreted as an order-volume-based classification rather than as a measure of revenue, number of employees, number of locations, or contract value.

Missing values were handled according to their substantive meaning. For behavioural count variables, missing observations after merging were set to zero only when the absence of a record could reasonably be interpreted as non-use within a company-quarter. This applied primarily to dashboard activity, support counts, standard-order counts, and incident and damage/malfunction counts. In contrast, contextual variables and performance indicators were not zero-filled, because missing values in these fields indicate absence of information rather than absence of behaviour.

This distinction follows the general principle that missing values should be interpreted in relation to the data-generating process and should not be automatically treated as zero observations (Little & Rubin, 2019).

6.3.5. Final analytical dataset

After cleaning, matching, aggregation, merging, normalisation, and missing-value handling, the final company-quarter dataset contained 1,415 observations and covered 196 unique companies. The dataset included routine order channel variables, dashboard engagement variables, support interaction variables, incident and damage/malfunction variables, total order volume, circular-performance indicators, contextual company characteristics, and derived relative engagement measures.

Because not all variables were observed for all companies and quarters, the effective number of observations differs across indicators and analyses. Analyses based only on engagement indicators can use more observations than analyses that also require circular-performance indicators. This is particularly relevant for the analysis of dashboard engagement and circular performance, because separation percentage, waste-related costs per kilogram, and CO₂-equivalent emissions per kilogram of waste are only available for a subset of company-quarter observations. The quantitative results therefore report the relevant sample size where necessary.

The final company-quarter dataset forms the empirical basis for analysing variation in multidimensional platform engagement. Where required, indicators are aggregated to the organisational level for analyses that compare organisations over the full observation period.

6.4. Operationalisation of multidimensional platform engagement

Building on the case-specific translation introduced in Chapter 5, organisational platform engagement is operationalised through four dimensions. These dimensions reflect observable forms of interaction with the Milgro platform and its related service infrastructure.

The four dimensions are not assumed to measure the same underlying behaviour. Instead, they capture different forms of platform interaction that may vary independently. Informational dashboard engagement captures the use of dashboard-based performance information. Routine transactional engagement captures recurring operational interactions. Support-related engagement captures interactions with service or support channels. Non-routine operational engagement captures exceptional or irregular operational interactions. From this point onwards, observable platform use is conceptualised as organisational platform engagement.

Figure 6.2 shows how the cleaned data sources are translated into operational indicators and analytical uses. The figure clarifies which data source contributes to each engagement dimension, which data source provides the circular-performance indicators, and how total order data are used for normalisation and customer-size grouping.

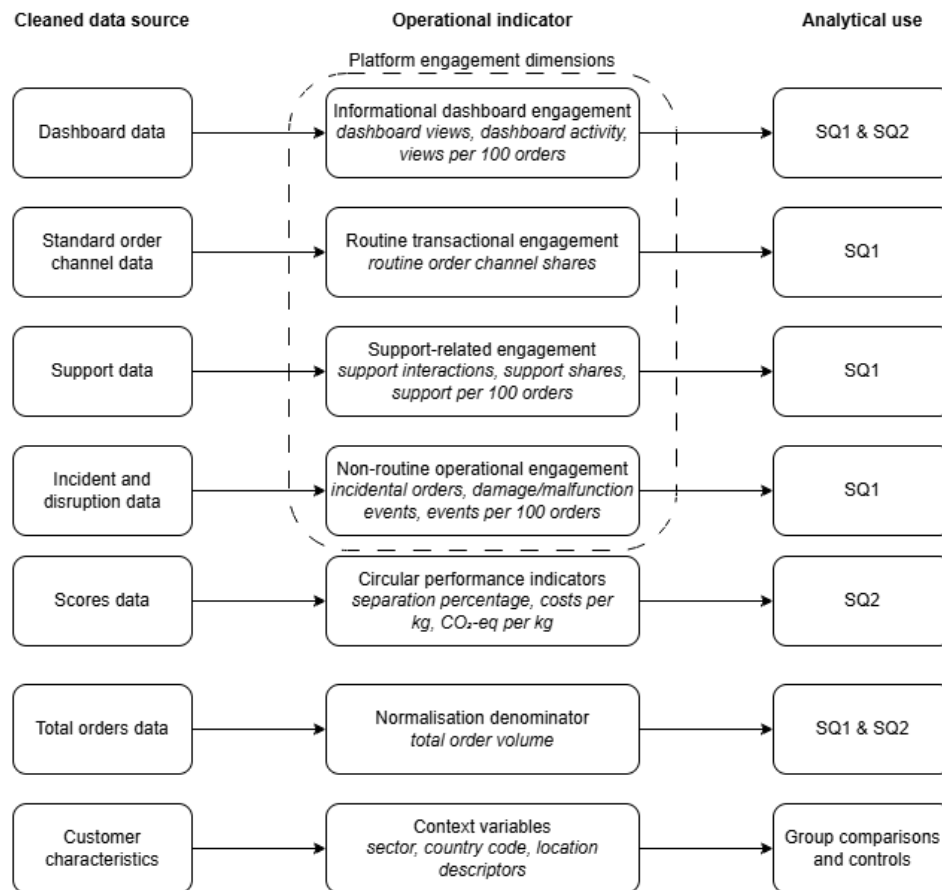


Figure 6.2: Operationalisation flow from cleaned data sources to engagement indicators, circular-performance indicators, and analytical use.

Figure 6.2 shows how the cleaned Milgro datasets are translated into operational indicators for the quantitative analysis. It also highlights that the four engagement dimensions are treated as distinct observable forms of platform interaction, rather than as one underlying engagement scale.

6.4.1. Informational dashboard engagement

Informational dashboard engagement refers to the use of dashboards and related platform functionalities through which organisations access waste-related and circular-performance information. This dimension is central to the second quantitative sub-question because dashboards provide the clearest interface between waste-related platform information and performance feedback.

Dashboard engagement is operationalised through two indicators: dashboard views per 100 orders and structural dashboard activity. Dashboard views per 100 orders capture the relative intensity of dashboard use in relation to the organisation's operational activity. Structural dashboard activity captures the consistency of dashboard use over time by measuring whether dashboard activity recurs across multiple quarters.

This distinction is analytically relevant. Occasional high-intensity dashboard viewing may reflect a different pattern of use than more consistent dashboard activity over time. The first may indicate incidental information checking, while the second may suggest more regular use of dashboard information. The quantitative data cannot determine the organisational meaning of these patterns, but they can show whether the patterns differ across organisations.

6.4.2. Routine transactional engagement

Routine transactional engagement refers to the use of standardised channels for recurring operational interactions, such as routine waste orders. This dimension captures how client organisations organise

regular waste-related processes.

Routine transactional engagement is operationalised through the distribution of standard orders across available order routes and systems. These may include portal-based orders, app-based orders, OBO orders, and orders processed through SLIMS. OBO refers to 'orders buiten ons om', meaning orders or tickets registered outside the regular order flow. SLIMS refers to Milgro's internal order-management system, which supports order processing and administrative handling.

The key indicators are the shares of standard orders registered through each route or system. These shares indicate the extent to which routine interactions are organised through digital platform channels or through alternative channels. They also make it possible to compare organisations with different order volumes.

6.4.3. Support-related engagement

Support-related engagement refers to interactions with Milgro or related service channels to resolve questions, uncertainties, or operational issues. These interactions form a separate dimension because they do not necessarily indicate the same type of platform use as dashboard activity or routine transactions.

Support-related engagement is operationalised through support interactions per 100 orders and support-channel shares. Support interactions per 100 orders capture the relative intensity of support use. Support-channel shares capture the distribution of support interactions across available channels, such as e-mail, telephone, portal, or chat.

The interpretation of support-related engagement requires caution. Higher support intensity may reflect active engagement with the platform and its service infrastructure. It may also reflect operational complexity, unclear processes, or a need for assistance. For this reason, support indicators are treated as descriptive and exploratory. Their organisational meaning is examined further in the qualitative phase.

6.4.4. Non-routine operational engagement

Non-routine operational engagement refers to exceptional or irregular interactions within the waste-management process. These include incidental orders and damage or malfunction-related events. This dimension captures how organisations deal with operational variation and unexpected situations.

Non-routine operational engagement is operationalised through incidental orders per 100 orders and damage or malfunction events per 100 orders. Where relevant, channel distributions are also used to describe how these interactions are registered or processed.

As with support-related engagement, these indicators should not be interpreted as straightforwardly positive or negative. A higher level of non-routine operational engagement may indicate greater operational complexity, more irregular waste-management needs, or more active registration of exceptional events. The quantitative phase identifies variation in these indicators, while the qualitative phase helps interpret their organisational meaning.

Table 6.2: Operationalisation of multidimensional platform engagement

Dimension	Empirical indicators	Analytical purpose
Informational dashboard engagement	Dashboard views per 100 orders; structural dashboard activity	Captures access to dashboard-based performance information
Routine transactional engagement	Shares of standard orders by order route or system, such as portal, app, OBO (<i>orders buiten ons om</i> ; orders or tickets outside the regular order flow), and SLIMS (Milgro's internal order-management system)	Captures how recurring operational interactions are organised
Support-related engagement	Support interactions per 100 orders; support-channel shares	Captures reliance on support or service interactions
Non-routine operational engagement	Incidental orders per 100 orders; damage/malfunction events per 100 orders; channel distribution where relevant	Captures exceptional or irregular operational interactions

6.5. Operationalisation of circular-performance indicators

Circular performance is operationalised through three indicators available in the Milgro data environment: waste separation percentage, waste-related costs per kilogram, and CO₂-equivalent emissions per kilogram of waste. These indicators capture different dimensions of circular performance.

Waste separation percentage reflects the extent to which waste is separated into streams that may enable recycling, reuse, or more effective processing. It is relevant because waste separation is a practical condition for many circular waste-management strategies.

Waste-related costs per kilogram capture the financial dimension of waste-management performance. This indicator provides insight into the cost intensity of waste-related processes. It is included because circular-performance improvement may also involve reducing inefficient or costly waste-management practices.

CO₂-equivalent emissions per kilogram of waste capture an environmental performance dimension. This indicator reflects the emissions associated with waste flows and processing routes, expressed relative to the amount of waste.

These indicators do not provide a complete measure of circular value creation. Circular performance is broader than waste separation, cost intensity, and CO₂-equivalent emissions. It may also involve prevention, reuse quality, material recovery value, behavioural change, or long-term system transformation. However, the three selected indicators represent relevant and available dimensions of circular performance within the Milgro data environment.

The interpretation of these indicators remains cautious. Circular-performance indicators may be influenced by sector, waste composition, location characteristics, operational processes, contract conditions, and external constraints. For this reason, the quantitative analysis explores associations between dashboard engagement and circular-performance indicators, but does not interpret these associations as causal effects.

Table 6.3: Operationalisation of circular-performance indicators

Indicator	Dimension captured	Interpretation
Waste separation percentage	Waste-stream separation	Indicates the extent to which waste is separated into streams that may support recycling, reuse, or more effective processing
Waste-related costs per kilogram	Financial waste-management performance	Indicates cost intensity relative to waste volume
CO ₂ -equivalent emissions per kilogram of waste	Environmental performance	Indicates emissions associated with waste flows and processing routes relative to waste volume

6.6. Quantitative analytical methods

The quantitative analysis is descriptive, comparative, and exploratory. It is designed to identify empirical patterns and associations that can inform the subsequent qualitative phase.

For the analysis of multidimensional platform engagement, descriptive statistics are used to map variation across client organisations. These include measures of central tendency, dispersion, and distributional shape. Visualisations such as histograms, boxplots, and heatmaps are used to examine skewness, outliers, and patterns across engagement dimensions.

Group comparisons are conducted where analytically meaningful. These comparisons may examine differences across sectors, customer-size categories, or other available organisational context variables. Because several engagement indicators are expected to be skewed, contain outliers, or include many zero observations, non-parametric tests are used for group comparisons. Kruskal-Wallis tests are applied when comparing distributions across multiple independent groups. Where relevant, post-hoc pairwise comparisons are used to identify which groups account for observed differences.

For the analysis of dashboard engagement and circular-performance indicators, Spearman rank correlations are used. Spearman correlation is appropriate because several variables are non-normally distributed and may be related in monotonic rather than strictly linear ways. This rank-based approach fits the exploratory purpose of the analysis.

Dashboard-intensity groups are also compared descriptively and, where relevant, through non-parametric tests. This makes it possible to examine whether organisations with different levels of dashboard engagement differ in their circular-performance indicators. In addition, exploratory regression models with basic contextual controls may be used as robustness checks. These models are not interpreted as causal identification strategies. They are used only to assess whether observed associations remain visible when basic organisational context is taken into account.

Where sets of related statistical tests are conducted, multiple-testing correction is applied to reduce the risk of overinterpreting statistically significant findings that may arise by chance. Overall, the quantitative analytical strategy is intended to identify meaningful empirical patterns and contrasts. These patterns provide the basis for the qualitative sampling strategy and for the integrated interpretation in later chapters.

6.7. Implications for interpretation and link to quantitative results

The data preparation process has several implications for the interpretation of the quantitative results. First, the analysis is based on harmonised organisational identifiers rather than raw company-name strings. This improves consistency across source systems, but it also means that the final dataset reflects methodological choices made during matching and entity resolution. To reduce the risk of misclassification, matching decisions were made conservatively and detailed procedures are documented in the appendices.

Second, engagement is not measured as a single variable. It is represented through multiple engineered indicators that capture intensity, consistency, channel composition, and irregularity of use. This supports the conceptualisation of engagement as a multidimensional construct and avoids

reducing platform engagement to one usage metric.

Third, the quantitative dataset captures observable behavioural traces, not the motivations or interpretations behind them. Dashboard views, support interactions, and channel shares indicate patterns of use, but they do not explain why users behave in certain ways or whether platform information is perceived as relevant for action. For this reason, the quantitative findings are interpreted in combination with the qualitative interview phase developed later in the thesis.

Fourth, the final dataset should be understood as a constructed analytical dataset rather than a direct extract of organisational behaviour. Raw operational records were transformed through cleaning, matching, aggregation, normalisation, missing-value handling, and indicator construction. These steps improved comparability and analytical usefulness, but they also require cautious interpretation. The quantitative results therefore show structured patterns in observable platform engagement, not complete explanations of organisational platform use.

The next chapter presents the quantitative results. It first maps variation in multidimensional platform engagement across client organisations. It then explores associations between informational dashboard engagement and circular-performance indicators. The patterns identified in this phase provide the empirical basis for the qualitative sampling strategy developed later in the thesis.

7 | Quantitative Results

This chapter presents the results of the quantitative phase. It first addresses how patterns of engagement with the Milgro platform vary across organisations. It then explores whether informational dashboard engagement is associated with available circular-performance indicators.

The first part of the chapter analyses platform engagement through relative indicators, including dashboard views per 100 orders, support tickets per 100 orders, incidental orders per 100 orders, damage or malfunction reports per 100 orders, and channel shares for routine orders. Relative indicators are used to reduce the risk that observed differences mainly reflect organisational scale rather than differences in platform-use patterns.

The chapter is structured as follows. Section 7.1 introduces the quantitative results. Section 7.2 provides a descriptive overview of the analytical dataset. Section 7.3 examines variation in multidimensional platform engagement. Section 7.4 analyses differences by sector and customer size. Section 7.5 explores associations between informational dashboard engagement and circular-performance indicators. Section 7.6 synthesises the quantitative findings. Section 7.7 explains how these findings inform the qualitative sampling strategy. Supplementary descriptive statistics, sector-level descriptives, customer-size comparisons, and diagnostic checks for SQ1 are reported in Appendix D. Supplementary descriptive statistics, correlation results, dashboard-intensity group comparisons, and exploratory regression checks for SQ2 are reported in Appendix E.

7.1. Introduction to the quantitative results

The quantitative results address two empirical sub-questions. SQ1 asks *How does the use of the digital circular-economy platform vary across organisations?* SQ2 asks *How is the use of performance dashboards associated with available circular-performance indicators?*

The analyses are descriptive, comparative, and exploratory. They do not establish causal relationships between platform engagement and circular-performance improvement. Instead, they identify patterns and associations that provide the empirical basis for the subsequent qualitative phase.

7.2. Descriptive overview of the analytical dataset

The quantitative analysis is based on the company-quarter dataset constructed in Chapter 6. The dataset covers the observation period from 2024Q1 to 2025Q4. It contains 1,415 company-quarter observations and 196 unique companies. The dataset includes indicators for routine transactional engagement, informational dashboard engagement, support-related engagement, non-routine operational engagement, total order volume, circular-performance indicators, and contextual company characteristics.

The effective number of observations differs across analyses because not all variables are available for all companies and quarters. Analyses based only on engagement indicators use a broader sample than analyses that require circular-performance indicators. This is particularly relevant for SQ2, where dashboard engagement is analysed in relation to separation percentage, waste-related costs per kilogram, and CO₂-equivalent emissions per kilogram of waste.

Supporting descriptive statistics for the main engagement indicators are reported in Appendix D.1. Additional channel-use descriptives are reported in Appendix D.2, while supplementary sector, customer-size, and location/country checks are reported in Appendices D.3–D.5. Descriptive statistics, missing-value checks, correlation results, dashboard-intensity group comparisons, and exploratory regression models for the dashboard-performance analysis are reported in Appendices E.1–E.4.

7.3. Variation in multidimensional platform engagement

This section addresses the first part of SQ1 by examining how platform engagement varies across organisations. It focuses on informational dashboard engagement, cross-dimensional engagement patterns, and channel patterns across engagement dimensions.

7.3.1. Uneven distribution of informational dashboard engagement

The first step is to examine whether organisations differ in their level of informational dashboard engagement. In line with the analytical framework in Chapter 4 and the operationalisation in Chapter 6, informational dashboard engagement refers to the use of dashboard functionalities that provide insight into waste flows, costs, and environmental performance. In this chapter, this dimension is measured primarily through dashboard views per 100 orders and dashboard activity.

The descriptive statistics reported in Appendix D.1 show that dashboard engagement is strongly right-skewed. The median is 5.29 dashboard views per 100 orders, while the mean is higher at 11.36 and the maximum reaches 328.62. This difference between the median, mean, and maximum indicates that dashboard use is concentrated among a small number of highly intensive users.

Although this section focuses on informational dashboard engagement, Appendix D.1 shows that skewness is also visible in other engagement indicators. For example, support intensity has a median of 5.37 support tickets per 100 orders, compared with a mean of 8.65 and a maximum of 100.00. This suggests that uneven engagement is not limited to dashboard use, but also appears in other platform engagement dimensions.

Figure 7.1 illustrates the distribution of informational dashboard engagement. Relative dashboard usage intensity is measured as the average number of dashboard views per 100 orders at the organisational level. A value close to zero means that an organisation hardly uses dashboards relative to its order volume, while higher values indicate more intensive dashboard use.

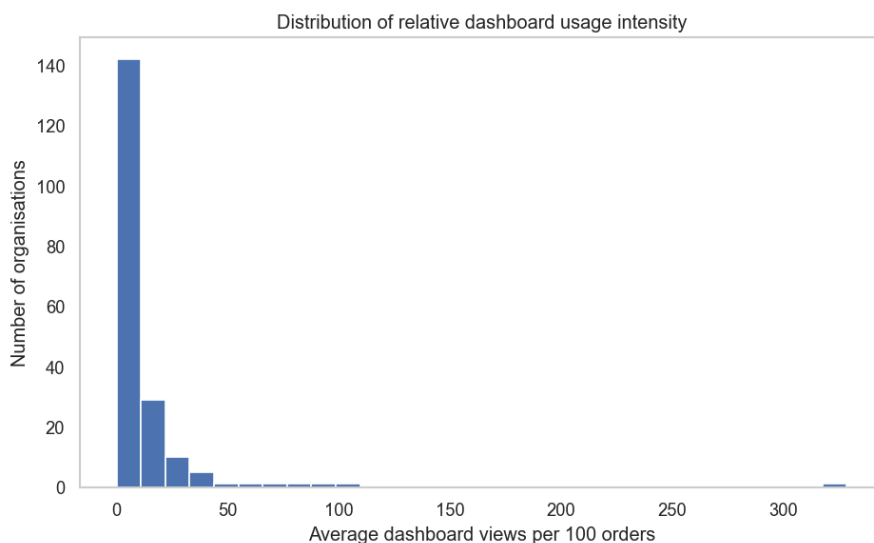


Figure 7.1: Distribution of relative dashboard usage intensity at the organisational level.

The distribution is concentrated at low values, with a long right tail. Most organisations are located in the lower part of the distribution: 25% of organisations record fewer than 1.12 dashboard views per 100 orders, and 50% record fewer than 5.29 dashboard views per 100 orders. By contrast, a limited number of organisations record much higher values, as shown by the maximum value of 328.62 dashboard views per 100 orders.

This confirms that informational dashboard engagement is not evenly distributed across the customer base. Most organisations show limited to moderate dashboard use, while a smaller group uses dashboards much more intensively. This provides an initial indication of substantial variation in

platform engagement. Dashboard functionality is available across the customer base, but it is not used uniformly.

7.3.2. Cross-dimensional engagement patterns

Organisational differences do not only concern the intensity of engagement, but also its composition. As introduced in Chapter 5 and operationalised in Chapter 6, this thesis treats platform engagement as multidimensional rather than as a single measure of platform use.

To examine whether this distinction is visible in the quantitative data, Figure 7.2 compares a selection of organisations across five engagement indicators: dashboard views per 100 orders, portal share of standard orders, support tickets per 100 orders, incidental orders per 100 orders, and damage or malfunction reports per 100 orders.

The heatmap reports column-standardised z-scores. Each indicator is standardised separately. A score of 0 represents the sample average for that specific indicator. Positive values indicate that an organisation scores above the sample average on that indicator, while negative values indicate below-average engagement. The values therefore show relative positions within each column and should not be interpreted as directly comparable absolute values across indicators.

In the heatmap, each row represents an anonymised organisation and each column represents one engagement indicator. The figure is anonymised by using organisation labels such as C01, C02, and C03 rather than company names.

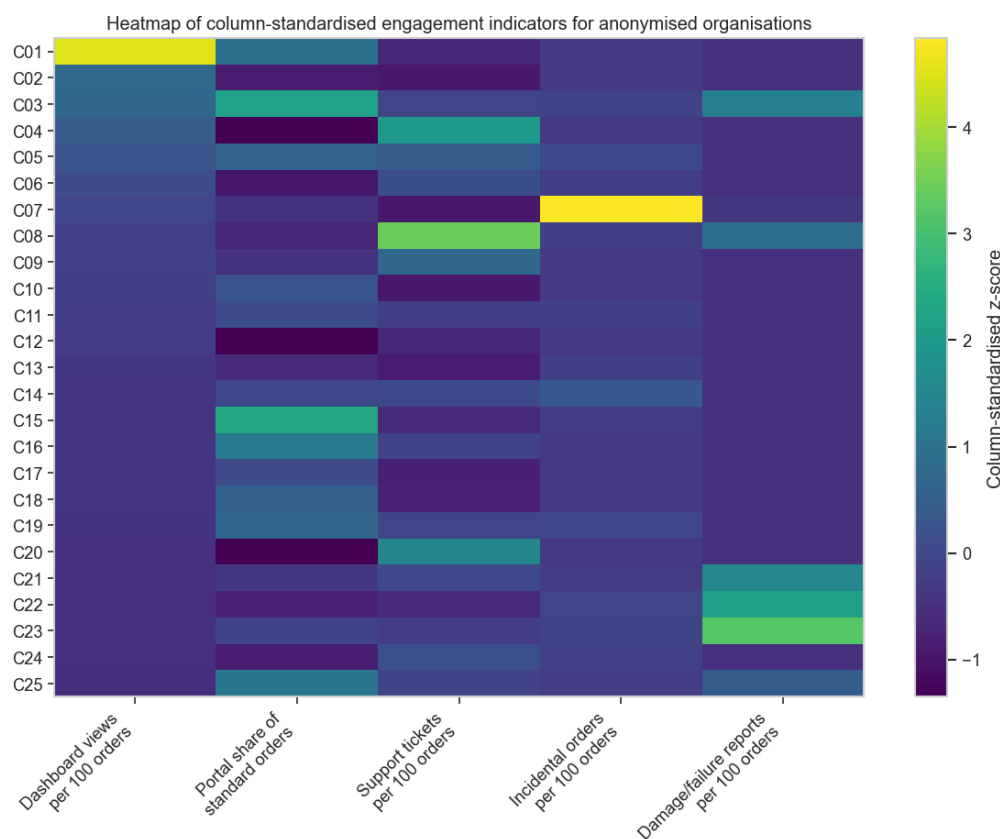


Figure 7.2: Heatmap of column-standardised engagement indicators by anonymised organisation. Values represent z-scores within each indicator; positive values indicate above-average scores and negative values indicate below-average scores.

The figure shows that organisational engagement cannot be reduced to one overall platform engagement indicator. Some organisations score relatively high on dashboard use but not on support or non-routine interactions. Others show high support intensity, incidental orders, or damage/malfunction

reporting while remaining closer to average on dashboard engagement. The portal share of standard orders also follows a different pattern from dashboard use and support interactions.

This pattern is in line with the multidimensional conceptualisation of platform engagement introduced in Chapter 5 and operationalised in Chapter 6. Rather than showing one uniform engagement scale, the heatmap shows variation across the predefined engagement dimensions: informational dashboard engagement, routine transactional engagement, support-related engagement, and non-routine operational engagement. High engagement in one dimension does not necessarily imply high engagement in another.

7.3.3. Channel patterns across engagement dimensions

The descriptive channel patterns reported in Appendix D.2 further support the multidimensional interpretation of engagement. Figure 7.3 visualises the mean channel shares across three engagement dimensions: routine transactional engagement, support-related engagement, and non-routine operational engagement.

In each panel, the vertical axis shows the mean share of interactions routed through each channel. A higher bar therefore means that, on average, a larger share of that type of interaction takes place through that channel. In the third panel, the legend distinguishes between incidental orders and damage/malfunction reports, because both are used as indicators of non-routine operational engagement.

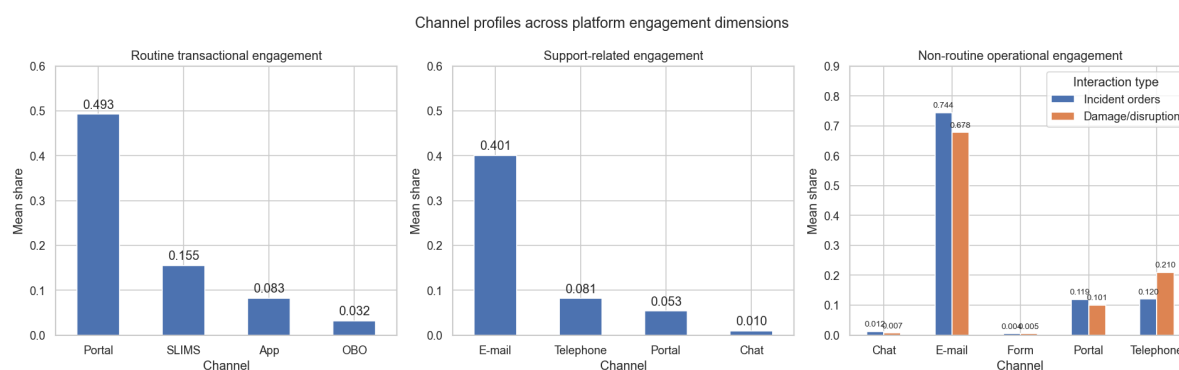


Figure 7.3: Channel profiles across platform engagement dimensions. The bars show mean channel shares within each engagement dimension. Routine transactional engagement is represented by standard-order channel shares, support-related engagement by support-ticket channel shares, and non-routine operational engagement by channel shares for incidental orders and damage/malfunction reports. In the third panel, the legend distinguishes between incidental orders and damage/malfunction reports.

Routine standard orders are mainly concentrated in structured digital channels, especially the portal and SLIMS (Milgro's internal order-management system). The portal accounts for the largest average share of standard orders, with a mean of 0.493 and a median of 0.522. SLIMS (Milgro's internal order-management system) is the second most important routine channel, with a mean share of 0.155. By contrast, the app and OBO (*orders buiten ons om*; orders or tickets outside the regular order flow) channels play a smaller role on average, with mean shares of 0.083 and 0.032 respectively.

Support interactions follow a different pattern. E-mail is the dominant support channel, with a mean share of 0.401 and a median of 0.439. Telephone support is used less intensively in terms of average share, with a mean of 0.081, but it remains more prominent than portal and chat support. Portal support has a mean share of 0.053, while chat has a mean share of only 0.010. This indicates that support-related engagement is not simply another form of routine platform use. It reflects a more problem-solving-oriented interaction pattern, in which organisations often rely on direct communication with the platform provider.

Non-routine operational interactions, such as incidental orders and damage/malfunction reports, are even more fragmented. E-mail is again the dominant channel, accounting on average for 0.744 of incidental orders and 0.678 of damage/malfunction reports. Other channels play a more selective role.

Portal and telephone are used by some organisations for non-routine interactions, but their median shares are often zero, meaning that many organisations do not use these channels at all for this type of interaction. The figure also shows that telephone is relatively more important for damage/malfunction reports than for incidental orders, with mean shares of 0.210 and 0.120 respectively.

Together, these channel patterns show that engagement differs not only in intensity, but also in form. Routine engagement is mainly organised through structured order channels, support-related engagement relies more strongly on direct communication, and non-routine engagement is more selective and organisation-specific. This supports the decision to treat platform engagement as a multidimensional construct rather than as a single usage measure.

7.4. Organisational differences in platform engagement

This section examines whether engagement patterns differ across organisational contexts. It focuses on sector and customer size, because these variables provide the most meaningful contextual comparisons in the available data. Additional diagnostic checks for location group and country code are reported in Appendix D.5.

7.4.1. Sectoral differences

The next step is to examine whether engagement patterns differ across sectors. Figure 7.4 shows the distribution of relative dashboard usage intensity by sector. Relative dashboard usage intensity refers to dashboard views per 100 orders. The figure is a boxplot: the horizontal line inside each box represents the sector median, the box shows the interquartile range, and the dots indicate outlying organisations with substantially higher relative dashboard use.

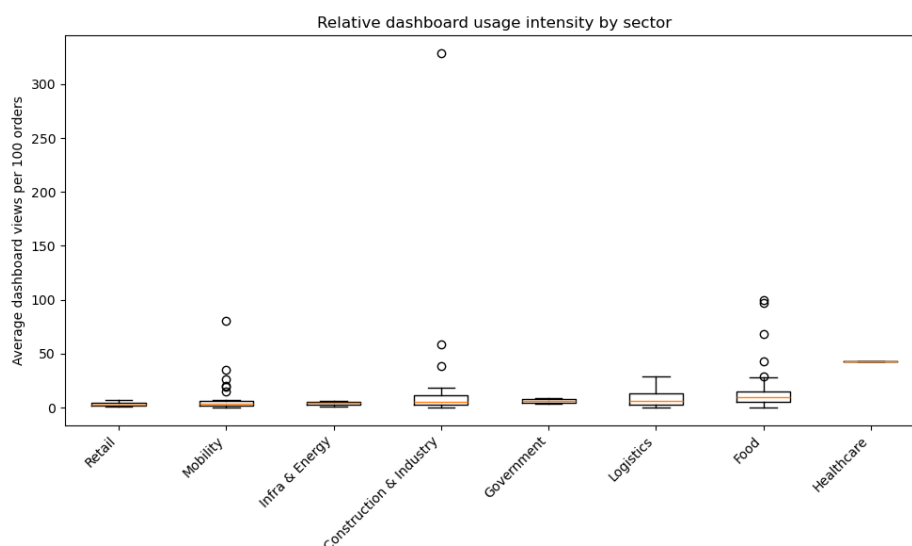


Figure 7.4: Relative dashboard usage intensity by sector

The boxplot shows that most sectors contain organisations with relatively low dashboard intensity, but the extent of variation differs. Construction Industry contains the most extreme high-intensity outlier, while Food and Mobility also contain several organisations with substantially higher dashboard use than the rest of their sector. Logistics shows a wider spread among the central group of organisations, but without the same extreme outlier pattern. Healthcare appears high in the figure, but this sector contains only one organisation in the dataset and should therefore not be interpreted as a robust sector-level pattern.

To assess whether sector differences are statistically visible, Kruskal-Wallis tests were conducted. The Kruskal-Wallis test examines whether the distribution of an engagement indicator differs across multiple independent groups. Because the data are skewed and contain outliers, this non-parametric test is more appropriate than a standard ANOVA.

Table 7.1 reports the most substantively relevant Kruskal-Wallis results for sector differences.

Table 7.1: Main Kruskal-Wallis results for engagement differences between sectors

Engagement indicator	Kruskal-Wallis H	p -value
Support tickets per 100 orders	26.78	< 0.001
SLIMS (Milgro's internal order-management system) share of standard orders	22.00	0.005
Dashboard views per 100 orders	18.80	0.009
Damage/malfunction reports per 100 orders	18.24	0.011
Incidental orders per 100 orders	16.75	0.019
Portal share of support tickets	17.56	0.025
Portal share of standard orders	15.84	0.045
App share of standard orders	15.83	0.045

The table shows that sector differences are statistically visible for several engagement indicators. The strongest difference is found for support tickets per 100 orders, $H = 26.78, p < 0.001$. Significant differences are also found for SLIMS (Milgro's internal order-management system) share of standard orders, $H = 22.00, p = 0.005$, dashboard views per 100 orders, $H = 18.80, p = 0.009$, damage/malfunction reports per 100 orders, $H = 18.24, p = 0.011$, and incidental orders per 100 orders, $H = 16.75, p = 0.019$. Sector differences are therefore not limited to dashboard use alone. They also appear in routine transactional engagement, support-related engagement, and non-routine operational engagement.

These results indicate that sector context is associated with several dimensions of platform engagement. For routine transactional engagement, differences are reflected in the channel allocation of standard orders, especially the SLIMS, portal, and app shares. This suggests that engagement is not only organisation-specific, but also related to the operational and sectoral context in which waste-management processes take place.

At the same time, these findings should be interpreted cautiously. Some sector groups are small, which means that outliers can strongly influence visual patterns and group means. The Kruskal-Wallis tests show that statistically visible differences exist across sectors, but they do not establish causal sector effects. The sector results are therefore used as descriptive and comparative evidence.

7.4.2. Customer-size differences

Customer size refers to the order-volume-based size classification introduced in Chapter 6. Organisations were divided into three tertiles based on their average total number of orders over the observation period, labelled small, medium-sized, and large. Customer size therefore captures relative operational scale within the dataset, rather than revenue, number of employees, number of locations, or contract value.

Figure 7.5 shows the distribution of relative dashboard usage intensity across customer-size classes. Because dashboard intensity is expressed per 100 orders, the figure compares relative dashboard use rather than absolute dashboard activity.

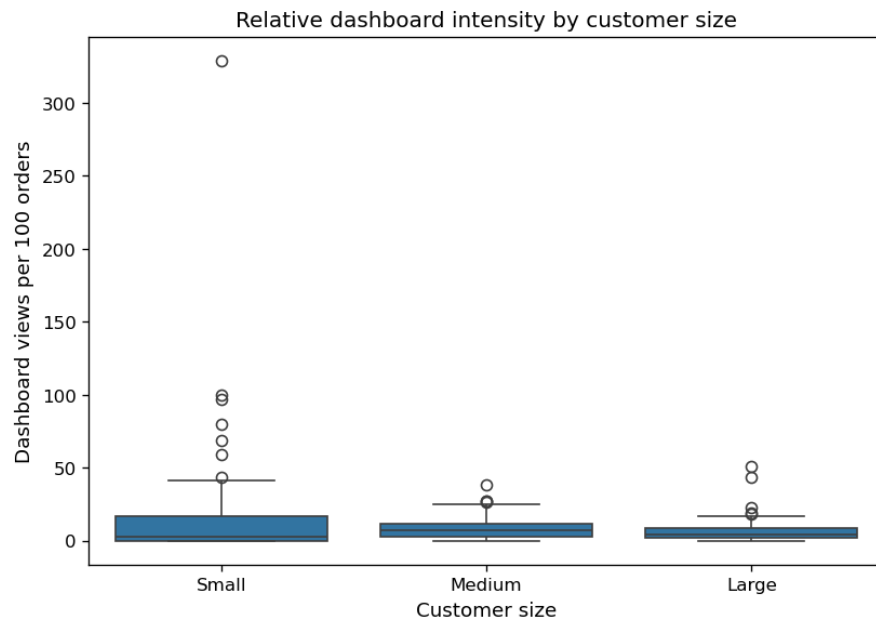


Figure 7.5: Relative dashboard usage intensity by customer size (order-volume tertile)

The figure shows that small organisations contain several high-intensity outliers. This means that some small organisations use dashboards very intensively relative to their order volume. However, the median values remain relatively low across all size groups. The boxplot should therefore be read as a distributional comparison rather than as a ranking of customer-size groups.

The Kruskal-Wallis results confirm this interpretation. Relative dashboard intensity does not differ significantly across customer-size classes, $H = 3.27, p = 0.195$. However, customer size is strongly associated with dashboard activity, $H = 68.79, p < 0.001$. This means that larger organisations are not necessarily more intensive dashboard users per 100 orders, but they are more consistently dashboard-active over time.

Table 7.2: Main Kruskal-Wallis results for engagement differences by customer size

Engagement indicator	Kruskal-Wallis H	p -value
Dashboard activity	68.79	< 0.001
OBO (orders or tickets outside the regular order flow) share of standard orders	46.61	< 0.001
Telephone share of support tickets	38.75	< 0.001
E-mail share of support tickets	35.41	< 0.001
App share of standard orders	33.85	< 0.001
Portal share of standard orders	29.98	< 0.001
Damage/malfunction reports per 100 orders	27.34	< 0.001
Chat share of support tickets	26.90	< 0.001
Portal share of support tickets	18.80	< 0.001
SLIMS (Milgro's internal order-management system) share of standard orders	12.52	0.002
Incidental orders per 100 orders	11.08	0.004
Dashboard views per 100 orders	3.27	0.195
Support tickets per 100 orders	0.41	0.814

The table shows that customer size is associated with several engagement indicators across multiple platform engagement dimensions. The strongest difference concerns dashboard activity, $H = 68.79, p < 0.001$. Significant differences are also visible for routine transactional engagement, reflected in the OBO (*orders buiten ons om*; orders or tickets outside the regular order flow), app, portal, and SLIMS (Milgro's internal order-management system) shares of standard orders. Support-related engagement differs mainly in channel composition, especially telephone and e-mail support shares. Non-routine operational engagement also differs by size, as shown by significant differences in damage/malfunction reports per 100 orders and incidental orders per 100 orders.

Importantly, two relative intensity indicators do not differ significantly by customer size: dashboard views

per 100 orders, $H = 3.27, p = 0.195$, and support tickets per 100 orders, $H = 0.41, p = 0.814$. Customer size is therefore not mainly associated with how intensively organisations use dashboards or support channels relative to order volume. Instead, it is more strongly associated with whether engagement is structurally present and how interactions are routed across channels.

Additional customer-size descriptives and post-hoc pairwise contrasts, reported in Appendix D.4, indicate that the main differences are generally between small organisations and medium-sized or large organisations. Small organisations tend to score lower on several structured channel-use indicators, whereas medium-sized and large organisations show more routinised engagement patterns.

These results indicate that customer size is associated with the form and consistency of platform engagement more than with relative intensity alone. Small organisations do not simply engage less. Their engagement appears more uneven and less standardised across platform engagement dimensions. Medium-sized and large organisations, by contrast, show more consistent dashboard activity and more structured routine and support-related channel use.

7.5. Dashboard engagement and circular-performance indicators

This section addresses SQ2: *How is the use of performance dashboards associated with available circular-performance indicators?* The analysis examines whether informational dashboard engagement is associated with circular performance at the organisational level. In line with the research design, the purpose is not to establish causal effects, but to identify indicative associations.

Two indicators of informational dashboard engagement are used. The first is relative dashboard intensity, measured as average dashboard views per 100 orders. This indicator captures dashboard use relative to order volume. The second is structural dashboard activity, measured as the share of quarters in which an organisation recorded at least one dashboard view. This indicator captures whether dashboard use is consistently present over time. Circular performance is measured through three indicators: waste separation percentage, waste-related costs per kilogram, and CO₂-equivalent emissions per kilogram of waste.

To reduce quarter-level noise and focus on structural differences between organisations, the variables are aggregated to the organisational level by averaging across the observation period. Descriptive statistics and missing-value checks are reported in Appendix E.1, Spearman correlation results in Appendix E.2, dashboard-intensity group comparisons in Appendix E.3, and exploratory regression models in Appendix E.4.

7.5.1. Descriptive overview of dashboard and performance indicators

The descriptive statistics reported in Appendix E.1 show that the dashboard engagement indicators have different distributions. Relative dashboard intensity is strongly right-skewed. The median is 5.29 dashboard views per 100 orders, while the mean is higher at 11.36 and the maximum reaches 328.62. This indicates that most organisations have relatively low dashboard intensity, while a small number of organisations record much higher values.

Structural dashboard activity shows a different pattern. The mean is 0.624 and the median is 0.813, meaning that many organisations are active in the dashboard in a substantial share of quarters. However, the spread remains large. Some organisations never record dashboard activity, while others are active in all observed quarters. This distinction matters because dashboard intensity captures relative viewing volume, while dashboard activity captures consistency over time.

Figure 7.6 visualises the distributions of the two dashboard engagement indicators. The left panel shows the right-skewed distribution of dashboard views per 100 orders. The right panel shows that structural dashboard activity is spread across the full range from 0 to 1. Together, the panels confirm that the two indicators capture different aspects of informational dashboard engagement.

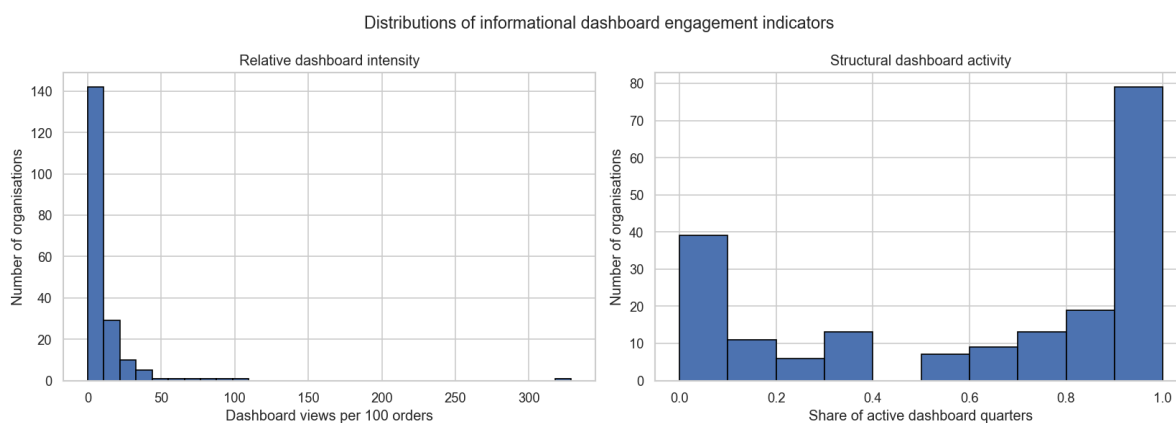


Figure 7.6: Distributions of informational dashboard engagement indicators. Relative dashboard intensity is measured as dashboard views per 100 orders. Structural dashboard activity is measured as the share of quarters in which an organisation recorded at least one dashboard view.

The circular-performance indicators also vary across organisations. The average separation percentage is 0.738, with a median of 0.789. Waste-related costs per kilogram have a mean of 0.193 and a median of 0.167. CO₂-equivalent emissions per kilogram of waste have a mean of 1.427 and a median of 1.359. Missing values are limited for the three performance indicators and are reported in Appendix E.1.

Figure 7.7 visualises the distributions of the three circular-performance indicators. Separation percentage is concentrated toward relatively high values, although a lower-performing group remains visible. Waste-related costs per kilogram and CO₂-equivalent emissions per kilogram are concentrated around lower values, with several higher observations.

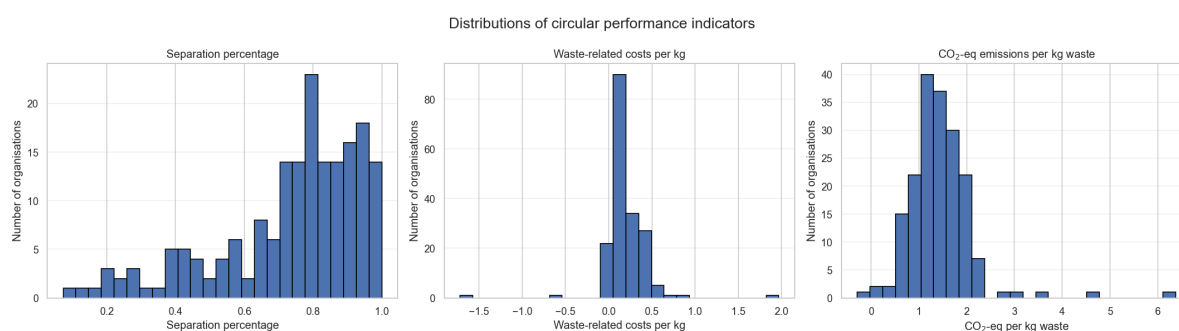


Figure 7.7: Distributions of circular performance indicators. The three panels show the organisational-level distributions of separation percentage, waste-related costs per kilogram, and CO₂-equivalent emissions per kilogram of waste.

These distributions indicate meaningful variation across organisations, but also skewness and outliers. This supports the use of rank-based correlations and non-parametric group comparisons in the following sections.

7.5.2. Bivariate associations

The first analytical step examines bivariate associations between the two dashboard engagement indicators and the three circular-performance indicators. Spearman correlations are used because the variables are not normally distributed and several indicators contain outliers. Spearman correlation is rank-based and is therefore suitable for assessing whether higher levels of dashboard engagement tend to coincide with higher or lower values of circular performance. The correlation results are reported in Appendix E.2.

Relative dashboard intensity is not significantly associated with any of the three circular-performance indicators after correction for multiple testing. Dashboard views per 100 orders are not significantly

associated with waste separation percentage, waste-related costs per kilogram, or CO₂-equivalent emissions per kilogram of waste.

Figure 7.8 visualises these associations. Each dot represents one organisation. The fitted lines do not show a clear or consistent relationship between relative dashboard intensity and the three performance indicators. Most organisations are clustered at low dashboard-intensity values, while a small number record much higher values. This visual pattern is consistent with the correlation results.

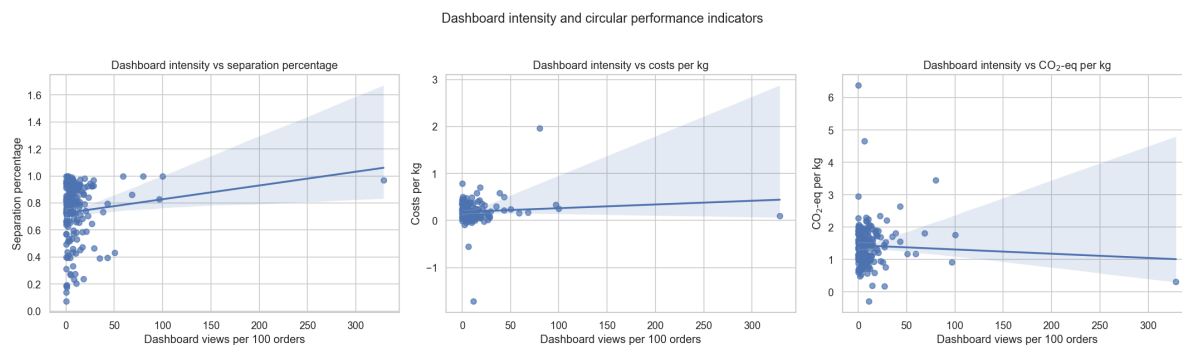


Figure 7.8: Associations between relative dashboard intensity and circular performance indicators at the organisational level. Relative dashboard intensity is measured as dashboard views per 100 orders. Each dot represents one organisation.

Structural dashboard activity shows a clearer pattern. The correlation results show two statistically significant bivariate associations after correction for multiple testing. Structural dashboard activity is positively associated with separation percentage, $\rho = 0.196, p_{\text{adj}} = 0.024$. It is negatively associated with waste-related costs per kilogram, $\rho = -0.336, p_{\text{adj}} < 0.001$. Structural dashboard activity is not significantly associated with CO₂-equivalent emissions per kilogram of waste.

Figure 7.9 visualises these associations for structural dashboard activity. Organisations with higher structural dashboard activity tend to show somewhat higher separation percentages and lower waste-related costs per kilogram. The spread around the fitted lines remains substantial. This means that structural dashboard activity is associated with some performance indicators, but does not explain them on its own. No clear visual pattern is visible for CO₂-equivalent emissions per kilogram of waste.

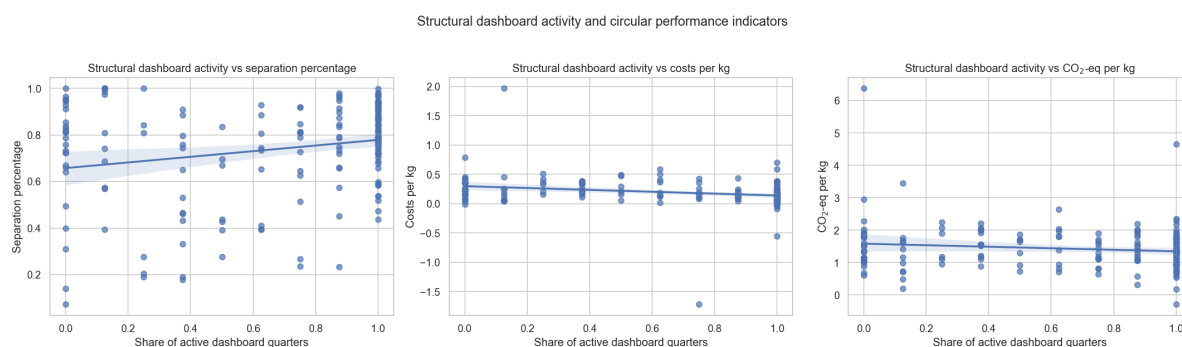


Figure 7.9: Associations between structural dashboard activity and circular performance indicators at the organisational level. Structural dashboard activity is measured as the share of quarters in which an organisation recorded at least one dashboard view. Each dot represents one organisation.

Taken together, the bivariate results suggest that structural dashboard activity is the more informative dashboard engagement indicator in this analysis. The consistency of dashboard use is more clearly associated with circular-performance indicators than the relative number of dashboard views per 100 orders.

7.5.3. Dashboard-intensity group comparisons

The previous section examined dashboard engagement as continuous variables. Because relative dashboard intensity is strongly skewed and influenced by a small number of high-intensity observations, a complementary group-based comparison was conducted. Organisations were divided into three dashboard-intensity groups based on tertiles of dashboard views per 100 orders: low, medium, and high intensity.

Figure 7.10 compares the distributions of the three circular-performance indicators across these dashboard-intensity groups. The boxplots show the median, interquartile range, and individual organisations in each group.

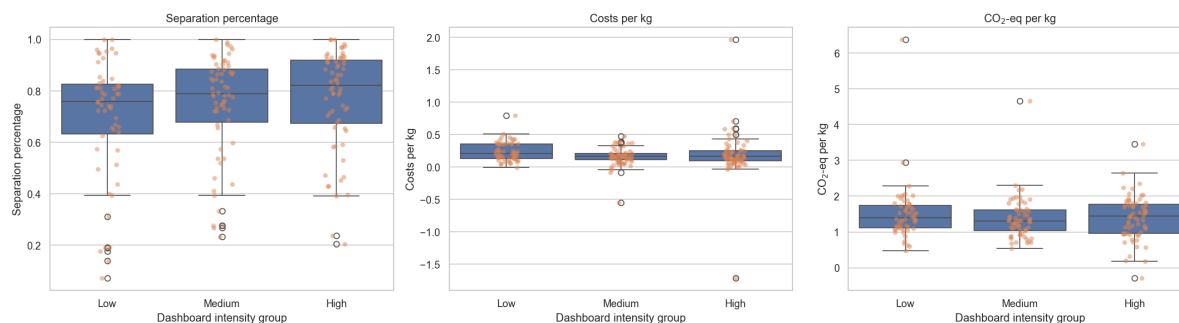


Figure 7.10: Distribution of circular performance indicators across low-, medium-, and high-intensity dashboard user groups. Dashboard-intensity groups are based on dashboard views per 100 orders.

The figure indicates a gradual increase in waste separation percentage across the three dashboard-intensity groups. The mean separation percentage increases from 0.697 in the low-intensity group to 0.744 in the medium-intensity group and 0.768 in the high-intensity group. However, the overlap between the groups remains substantial. Dashboard-intensity group membership therefore does not clearly separate organisations with high and low separation performance.

For waste-related costs per kilogram, the medium-intensity group has the lowest mean value. Mean costs decrease from 0.240 in the low-intensity group to 0.158 in the medium-intensity group, before increasing to 0.186 in the high-intensity group. This suggests a descriptive difference, but not a simple linear pattern in which higher dashboard intensity is consistently associated with lower costs.

For CO₂-equivalent emissions per kilogram of waste, the distributions overlap strongly. The group means are 1.518 for the low-intensity group, 1.375 for the medium-intensity group, and 1.399 for the high-intensity group. This does not indicate a clear systematic shift across dashboard-intensity groups.

The Kruskal-Wallis tests reported in Appendix E.3 show that none of these group differences remain statistically significant after correction for multiple testing. For waste-related costs per kilogram, the unadjusted result is suggestive, $p = 0.019$, but this does not remain significant after correction, $p_{\text{adj}} = 0.058$. No pairwise post-hoc tests were therefore performed.

Overall, the grouped comparison points to modest descriptive differences, especially for separation percentage and waste-related costs per kilogram. These differences are not robust enough to be interpreted as statistically reliable. This reinforces the earlier finding that relative dashboard intensity provides limited evidence of association with circular performance.

7.5.4. Exploratory contextual checks

The final analytical step examines whether the bivariate associations remain visible once basic contextual differences are taken into account. Exploratory regression models were estimated with controls for customer size and sector. Each circular-performance indicator was regressed on one dashboard engagement indicator at a time, while including customer size and sector as contextual controls. Customer size was operationalised through tertiles of average total order volume, as described in Chapter 6.

These models are not interpreted causally. They are used only to assess whether the main dashboard-performance associations remain visible when basic organisational context is included.

The regression results are reported in Appendix E.4. None of the informational dashboard engagement predictors remain statistically significant after correction for multiple testing. For waste separation percentage, the positive bivariate association with structural dashboard activity weakens once controls are added. For waste-related costs per kilogram, the coefficient for structural dashboard activity remains negative, but is not statistically significant in the controlled specification. No meaningful controlled relationship is found for CO₂-equivalent emissions per kilogram of waste.

These results suggest that the bivariate associations are partly related to broader organisational and contextual differences. Informational dashboard engagement may be associated with circular-performance indicators, but it should not be interpreted independently of customer size, sector, operational routines, and other organisational conditions. This supports the cautious interpretation of the quantitative results and reinforces the need for the qualitative phase to examine the organisational and socio-technical conditions behind these patterns.

7.6. Quantitative synthesis

The quantitative findings provide two main results. First, organisational engagement with the Milgro platform is uneven, multidimensional, and context-dependent. Second, the relationship between informational dashboard engagement and circular-performance indicators is limited and conditional. Together, these findings show that observable platform use cannot be interpreted as a direct indicator of organisational action for circular-performance improvement.

For SQ1, the results show that engagement varies substantially across organisations, not only in amount but also in form and consistency. Dashboard use is concentrated among a limited subset of more intensive users. Organisations also differ across the four predefined engagement dimensions: informational dashboard engagement, routine transactional engagement, support-related engagement, and non-routine operational engagement. These dimensions do not move together consistently. Organisations that use dashboard information intensively are not necessarily the same organisations that place routine waste orders through digital platform channels, rely heavily on support interactions, or generate many non-routine operational interactions. Dashboard use should therefore not be treated as a proxy for overall platform engagement.

Engagement also varies across organisational contexts. Sector differences are visible across several engagement indicators. Customer size, understood as order-volume-based operational scale, is associated mainly with the consistency and form of engagement rather than with relative dashboard intensity. Dashboard views per 100 orders do not differ significantly by customer size, while dashboard activity does. This suggests that larger organisations are not necessarily more intensive dashboard users relative to order volume, but they are more consistently dashboard-active over time.

For SQ2, the results show that dashboard intensity is not statistically robustly associated with circular-performance indicators. Relative dashboard intensity, measured as dashboard views per 100 orders, does not significantly coincide with higher waste separation, lower waste-related costs, or lower CO₂-equivalent emissions per kilogram of waste after correction for multiple testing. This indicates that dashboard intensity mainly captures access to dashboard information, rather than whether that information is interpreted, embedded, or followed up in organisational practice.

Structural dashboard activity provides a more informative but still context-dependent pattern. Organisations that are active in the dashboard across a larger share of quarters tend to show higher waste separation percentages and lower waste-related costs per kilogram in the bivariate analysis. However, these associations weaken when customer size and sector are included as contextual controls. The grouped dashboard-intensity comparison also shows only modest descriptive differences, particularly for waste separation percentage and waste-related costs per kilogram. These differences do not remain statistically significant after correction for multiple testing.

Overall, the quantitative findings suggest that the consistency of dashboard activity may be more relevant than the number of dashboard views per 100 orders. This interpretation remains cautious. The quantitative data show observable patterns and associations, but they cannot explain why organisations

use different platform functionalities in different ways. Nor can they determine whether structural dashboard activity reflects embedded monitoring routines, reporting cycles, managerial attention, data validation, or other organisational conditions. These questions are addressed in the qualitative phase, where interviews are used to explain the socio-technical conditions behind the observed platform-use and circular-performance patterns.

7.7. Implications for qualitative sampling

The quantitative results provide the empirical basis for the qualitative sampling strategy. The SQ1 findings show that platform engagement varies across organisations in uneven, multidimensional, and context-dependent ways. The SQ2 findings show that structural dashboard activity is more clearly associated with some circular-performance indicators than relative dashboard intensity, but that these associations are limited and context-sensitive. The qualitative phase therefore focuses on organisations with contrasting dashboard engagement and circular-performance profiles. This sampling logic makes it possible to examine why similar levels of dashboard engagement may have different organisational meanings, and why platform information may or may not become connected to organisational follow-up in different organisational contexts. The next chapter explains the qualitative research design, including the interview sampling strategy, interview guide, thematic analysis approach, and integration with the quantitative findings.

8 | Qualitative Research Design

Chapter 7 presented the quantitative results. It showed that platform engagement varies across organisations in uneven, multidimensional, and context-dependent ways. It also showed that informational dashboard engagement is selectively associated with circular-performance indicators, with structural dashboard activity appearing more informative than relative dashboard intensity.

This chapter explains how the qualitative phase was designed to build on these quantitative findings. The qualitative phase does not introduce a new case. Instead, selected client organisations are studied as embedded units of analysis within the broader single-case study of the Milgro platform ecosystem. The purpose of the qualitative phase is to provide explanatory depth by examining how the quantitative patterns can be understood in organisational practice.

The chapter is structured as follows. Section 8.1 explains the purpose of the qualitative phase. Section 8.2 describes the construction of the organisation-level selection frame. Section 8.3 explains the interview sampling strategy. Section 8.4 presents the realised interview sample. Section 8.5 describes the interview design and data collection. Section 8.6 explains the qualitative coding and thematic analysis. Section 8.7 discusses how the qualitative phase is integrated with the quantitative findings. Section 8.8 summarises the chapter and links it to the qualitative results.

8.1. Purpose of qualitative phase

The qualitative phase follows directly from the sequential explanatory mixed-methods design introduced in Chapter 2. The quantitative phase identified patterns in platform engagement and explored associations between dashboard engagement and circular-performance indicators. However, platform data alone cannot explain how users understand dashboard information, how platform information is used in organisational practice, or why similar quantitative patterns may have different organisational meanings.

The qualitative phase therefore addresses the sub-questions concerned with user perceptions and socio-technical conditions. SQ3 focuses on how organisational users understand, interpret, and evaluate dashboard information, including its perceived usefulness, relevance, and practical meaning. SQ4 focuses on which organisational and external conditions may facilitate or hinder the translation of platform information into organisational follow-up within a business-to-business waste-value ecosystem.

The interviews are used to interpret and contextualise the quantitative findings. They examine how dashboard and platform information is understood by organisational users, how it is connected to routines and responsibilities, and how organisational or ecosystem-level conditions may shape follow-up. In this way, the qualitative phase performs the explanatory function of the mixed-methods design.

8.2. Construction of the organisation-level selection frame

The interview selection was based on the quantitative results presented in Chapter 7. To construct the selection frame, the integrated company-quarter dataset was aggregated to the organisational level. Each organisation was represented by average values for dashboard engagement, circular-performance indicators, customer size, sector, and supplementary engagement indicators over the observation period.

The selection frame combined indicators of informational dashboard engagement with indicators of circular performance. Informational dashboard engagement was captured through relative dashboard intensity and structural dashboard activity. Relative dashboard intensity refers to average dashboard views per 100 orders. Structural dashboard activity refers to the share of quarters in which an

organisation recorded at least one dashboard view.

Circular performance was captured through waste separation percentage and waste-related costs per kilogram. Lower costs per kilogram were interpreted as better performance in this selection logic. CO₂-equivalent emissions per kilogram were retained descriptively, but not used to construct the primary performance profile, because the quantitative results did not show a clear association between dashboard engagement and this indicator.

Based on these indicators, organisations were assigned to relative engagement and performance profiles. These profiles formed the basis for the purposive interview sampling strategy. The full construction of the selection frame and the distribution of profile types before filtering are reported in Appendix F.1.

8.3. Interview sampling strategy

The interview sampling strategy was purposive. The aim was not to construct a statistically representative sample of all Milgro client organisations, but to select organisations that were analytically informative for explaining the quantitative patterns. This follows the logic of information-rich case selection (Patton, 2015).

The primary sampling criterion was contrast in dashboard engagement and circular performance. Organisations were classified into five engagement-performance profile types:

- High engagement/High performance
- High engagement/Low performance
- Low engagement/High performance
- Low engagement/Low performance
- Mixed/intermediate

This classification was designed to support contrast-based comparison. Comparing organisations with different engagement-performance profiles can help examine why similar dashboard engagement patterns may coincide with different performance outcomes, or why similar performance outcomes may occur under different dashboard engagement conditions (Eisenhardt, 1989; Yin, 2018).

The high engagement / high performance profile captures organisations in which informational dashboard engagement and circular performance appear to align positively. The high engagement / low performance profile identifies organisations with substantial dashboard engagement but weaker circular-performance indicators. The low engagement / high performance profile captures organisations with relatively low dashboard engagement but stronger circular-performance indicators. The low engagement / low performance profile captures organisations that score relatively low on both dimensions. Mixed or intermediate organisations were retained because many organisations do not fall neatly into one of the four contrast profiles.

The sampling strategy also considered sector and customer size. This helped account for the sectoral and order-volume-based differences identified in Chapter 7. The realised sample was therefore assessed not only in terms of dashboard engagement and circular performance, but also in terms of sectoral and organisational diversity.

8.4. Recruitment and realised interview sample

Before organisations were approached, two restrictions were applied to the organisation-level selection frame. The initial selection frame contained 196 organisations. First, organisations without a known sectoral cluster were excluded. Sector context was relevant because the quantitative results showed that platform engagement differs across sectors. After this restriction, 166 organisations remained.

Second, only organisations with observable dashboard presence were retained. Organisations had to show at least some recorded dashboard activity during the observation period. Organisations without observable dashboard presence were excluded because it was not possible to distinguish

substantively meaningful non-use from missing or non-recorded dashboard data. After this restriction, 153 organisations remained in the candidate pool.

Within this candidate pool, 58 organisations fell into one of the four main contrast profiles. The remaining 95 organisations were classified as mixed or intermediate. Because participation could not be assumed in advance, recruitment was broader than the intended analytical sample. Organisations in the four main contrast profiles were approached, and additional mixed or intermediate organisations were contacted to increase the likelihood of sufficient sectoral and organisational variation in the realised sample. The filtered candidate pool by interview case type is reported in Appendix F.2.

The realised interview sample consisted of sixteen organisations. These organisations were selected for analytical variation rather than statistical representativeness. The sample includes organisations from all four main contrast profiles, as well as mixed or intermediate cases. It also covers all eight sectoral clusters and includes small, medium-sized, and large organisations.

Customer size was operationalised in the same way as in the quantitative analysis. For each organisation, the average total number of orders over the observation period was calculated. Organisations were then divided into three equally sized groups using tertiles of average order volume: small, medium-sized, and large. Customer size therefore reflects relative operational scale within the observed dataset, not revenue, number of employees, number of locations, or contract value.

Table 8.1: Composition of the realised interview sample

Dimension	Category	Number of organisations
<i>Engagement-performance profile type</i>		
	High engagement / High performance	5
	High engagement / Low performance	4
	Low engagement / High performance	1
	Low engagement / Low performance	2
	Mixed/intermediate	4
<i>Sector</i>		
	Food	4
	Construction & Industry	3
	Logistics	3
	Mobility	2
	Government	1
	Healthcare	1
	Infra & Energy	1
	Retail	1
<i>Customer size</i>		
	Small	2
	Medium	5
	Large	9
	Total	16

The realised sample reflects both the analytical sampling strategy and practical constraints of interview recruitment. The mixed or intermediate cases partly reflect non-response among some contrast profiles, but they also serve an analytical purpose. They broaden the sectoral and organisational diversity of the qualitative phase and reduce the risk of interpreting the quantitative results only through extreme cases.

Large organisations are overrepresented in the realised sample. This should be considered when interpreting the qualitative findings. At the same time, the inclusion of small and medium-sized organisations makes it possible to compare how dashboard use is interpreted across different levels of operational scale.

The realised sample also shows variation across the broader platform-engagement dimensions identified in Chapter 7. It includes organisations with different levels of support-related engagement, routine transactional engagement, and non-routine operational engagement. Additional descriptive checks of broader engagement variation in the realised interview sample are reported in Appendix F.3. The interview guide is included in Appendix H.

In the reporting of interview findings, organisations are anonymised. Company names were used only

during the internal recruitment and selection process and are not reported as identifiable organisation labels.

8.5. Interview design and data collection

Semi-structured interviews were used because they allow respondents to explain their experiences, interpretations, and organisational context in their own words, while still ensuring comparability across interviews (Kallio et al., 2016). This format was appropriate because the qualitative phase aimed to explain quantitative patterns without limiting respondents to predefined answer categories.

The interview guide was informed by the literature-based analytical framework developed in Chapter 4 and by the quantitative findings presented in Chapter 7. The guide included questions on general platform use, dashboard use, interpretation of dashboard information, perceived usefulness and relevance, data limitations, organisational routines, responsibilities, barriers to follow-up, and external or sector-specific conditions. The guide also allowed room for respondents to introduce case-specific explanations.

Particular attention was paid to dashboard use because dashboards provide the most direct link between platform information, performance feedback, and the circular-performance indicators analysed in Chapter 7. However, the interviews also addressed broader platform use. This was necessary because Chapter 7 showed that platform engagement is multidimensional and that dashboard use may be related to other forms of interaction, such as support contact, routine order channels, or non-routine operational events.

Where relevant, profile-specific probes were used. For example, organisations with high dashboard engagement but weaker performance indicators were asked how dashboard information was used and why follow-up might be difficult. Organisations with lower dashboard engagement but stronger performance indicators were asked whether alternative routines, information sources, or organisational practices supported circular performance. These probes were used to explore the meaning of the quantitative profiles, not to assume in advance that any profile had a single explanation.

The interviews were conducted online using Microsoft Teams. Prior to the interviews, participants received information about the purpose of the research, and informed consent was obtained in line with the ethical requirements and procedures of the TU Delft Human Research Ethics Committee (HREC). The informed consent form used for the interview phase is included in Appendix G. The interviews were recorded and initially transcribed using the transcription function in Microsoft Teams. The transcripts were then checked manually by listening back to the recordings and correcting transcription errors, unclear wording, and speaker-attribution issues where necessary.

8.6. Qualitative coding and thematic analysis

The interview transcripts were analysed using ATLAS.ti (Version 26), a qualitative data-analysis software package that supports the systematic coding, organisation, and retrieval of qualitative material (ATLAS.ti Scientific Software Development GmbH, 2026). ATLAS.ti was used to attach codes to relevant text fragments, organise codes into code families, and compare coded material across interviews.

The analysis followed a combined deductive and inductive thematic coding approach. This approach was chosen because the qualitative phase had a clear explanatory role within the sequential mixed-methods design, while still allowing themes to emerge from the interview material (Braun & Clarke, 2006; Fereday & Muir-Cochrane, 2006).

Deductive coding was guided by the analytical framework and the qualitative sub-questions. Codes related to dashboard and platform use, perceived usefulness, relevance, understandability, trust, and data limitations were used to examine user-level conditions. Codes related to organisational routines, responsibilities, decision-making, coordination, and barriers were used to examine organisational conditions. Codes related to sectoral context, external dependencies, reporting expectations, and inter-organisational coordination were used to examine ecosystem and institutional conditions.

Inductive coding was used to capture recurring themes that were not fully anticipated by the initial

coding structure. This kept the analysis open to case-specific explanations. Inductive codes were added when respondents described patterns or distinctions that were relevant to the research question but not fully captured by the initial code families.

Coding was conducted at the level of meaningful text fragments rather than individual sentences. A fragment could consist of one answer, part of an answer, or a short passage in which a respondent discussed a specific issue. Where relevant, multiple codes were assigned to the same fragment. This allowed the analysis to capture overlap between themes, for example when a respondent linked dashboard use to reporting requirements, organisational responsibility, and barriers to follow-up in the same passage.

After coding, the coded material was synthesised in two steps. First, within-organisation summaries were prepared for each interviewed organisation. These summaries described the organisation’s main forms of dashboard and platform use, perceived usefulness, data limitations, organisational embedding, responsibility structure, barriers, and contextual conditions. Second, the organisations were compared across engagement-performance profile type, sector, and customer-size category. This cross-organisation comparison was used to identify recurring explanatory patterns across the realised sample.

Table 8.2 provides an illustrative overview of the coding structure used in the qualitative analysis. The table does not report the full codebook. It shows how the main code families were translated into more specific subcodes and linked to the analytical purpose of the qualitative phase. The full codebook is reported in Appendix I.1.

Table 8.2: Illustrative coding structure for the qualitative analysis

Main code family	Example subcodes	Description	Illustrative quote
SQ3 – Dashboard and platform use	Dashboard use for reporting Dashboard use for monitoring	Captures how organisations use the platform or dashboard in practice, for example for reporting, KPI monitoring, operational checks, or ad hoc information retrieval.	"I mainly use the dashboard reports every month for the KPI reports."
SQ3 – Perceived usefulness	Dashboard provides insight Reporting efficiency	Captures whether respondents perceive dashboard information as useful, valuable, accessible, or supportive for reporting and understanding waste flows.	"I find it a very useful dashboard. That we use it little is not due to the quality of the dashboard."
SQ3 – Actionability	Dashboard triggers action Dashboard provides insight, not direct action	Captures whether dashboard information leads to concrete follow-up, internal discussion, business cases, or operational change.	"We saw the costs for almond skins increasing, so we are now looking at an investment to address those costs."
SQ3 – Data limitations	Data timeliness problem Definition mismatch	Captures limitations in dashboard data, including delays, incomplete coverage, unclear definitions, missing context, or insufficient granularity.	"For reporting, it is very unfavourable that figures are still changed later."
SQ4 – Organisational embedding	Embedded management routine Lack of operational routine	Captures whether dashboard use is embedded in meetings, reporting cycles, management reviews, operational routines, or remains incidental.	"It comes back in our management meeting, where we monitor it every quarter."
SQ4 – Ownership and responsibility	Formal ownership Monitoring-action split	Captures how responsibility for monitoring, interpretation, decision-making, and follow-up is distributed across people, departments, or locations.	"I monitor it, but responsibility for taking action lies with the department itself."
SQ4 – Barriers	Priority constraint Capacity constraint	Captures organisational and practical barriers that limit dashboard use or the translation of information into action.	"It is not that we sit down every quarter with the Milgro figures to see where we can improve."
SQ4 – Sector and contextual conditions	Food-specific constraints Limited operational predictability	Captures sector-specific and operational conditions that shape dashboard use and circular-performance improvement.	"Our planning is only ready at one o'clock, so we cannot look two or three days ahead."
SQ4 – External dependencies	Supplier dependency Supply-chain collaboration	Captures dependencies on suppliers, customers, contractors, processors, regulators, or Milgro for data, interpretation, or improvement.	"You need to get the rest of the chain on board if you want to take steps."
IND – Emergent codes	Provider-supported contextual translation Insight-action gap	Captures inductive patterns that emerged during coding and were used to refine the cross-organisation interpretation.	"The tool is then used more by Milgro itself, which gives advice based on process knowledge."

8.7. Integration with quantitative findings

Integration between the quantitative and qualitative phases occurs in three ways. First, integration occurs through sampling. The quantitative results were used to identify organisations with contrasting dashboard engagement and circular-performance profiles. This ensured that the qualitative phase was directly connected to the empirical patterns identified in Chapter 7.

Second, integration occurs during analysis. Interview findings are interpreted in relation to each organisation's observed quantitative profile, including dashboard activity, dashboard intensity, broader platform-engagement indicators, and circular-performance indicators. This makes it possible to compare observable platform behaviour with how respondents explain and interpret their own use of platform information.

Third, integration occurs in the final synthesis of the thesis. The quantitative findings identify patterns in platform engagement and dashboard-performance associations. The qualitative findings examine how these patterns can be understood in organisational and ecosystem context. The final discussion integrates both phases to answer the main research question and refine the literature-based analytical framework.

The qualitative phase therefore does not simply illustrate the quantitative findings. It provides the explanatory component of the mixed-methods design by examining how platform information is interpreted, embedded, and potentially connected to organisational follow-up in different organisational

contexts.

8.8. Summary and link to qualitative results

This chapter described the qualitative research design. It explained how organisations were selected for interviews based on the quantitative results, how the realised sample was composed, how interviews were designed and conducted, and how the interview material was coded and analysed.

The qualitative phase builds on the quantitative findings in two ways. It uses contrasting engagement-performance profiles to guide case selection, and it interprets interview findings in relation to each organisation's observed platform-engagement and performance profile. This creates a direct link between the quantitative patterns identified in Chapter 7 and the qualitative explanations presented in the next chapter.

Chapter 9 presents the qualitative findings. It examines how organisational users understand dashboard and platform information, how this information is embedded in organisational practice, and which organisational or external conditions may facilitate or hinder follow-up.

9 | Qualitative Results

This chapter presents the qualitative interview findings. It examines how organisations use, interpret, and embed waste-related platform and dashboard information in practice. Building on the qualitative research design described in Chapter 8, the analysis draws on sixteen interviewed organisations across five engagement-performance profiles.

The purpose of the chapter is not to describe each interviewed organisation separately. Instead, it identifies recurring qualitative patterns that help explain why dashboard engagement becomes connected to organisational follow-up in some organisations, while remaining mainly informational, report-oriented, or weakly embedded in others. Interviewed organisations are referred to using anonymised labels.

This chapter addresses the two qualitative sub-questions of the thesis. SQ3 asks *How do organisational users understand, interpret, and evaluate dashboard information?* SQ4 asks *Which organisational and ecosystem-level conditions facilitate or hinder the use of platform information for organisational follow-up within a business-to-business waste-value ecosystem?*

The chapter follows the analytical framework developed in Chapter 4. Section 9.1 introduces the qualitative findings. Section 9.2 discusses how the platform and dashboards are used in practice. Section 9.3 examines user-level conditions, focusing on perceived usefulness, actionability, data confidence, and contextual interpretation. Section 9.4 analyses organisational conditions, including routines, ownership, and responsibility. Section 9.5 discusses ecosystem and external conditions. Section 9.6 compares the engagement-performance profiles. Section 9.7 synthesises the qualitative findings and links them to the integrated discussion in Chapter 10.

9.1. Introduction to the qualitative findings

The quantitative results showed that platform engagement is uneven, multidimensional, and context-dependent. They also showed that informational dashboard engagement is selectively, rather than uniformly, associated with circular-performance indicators. The qualitative findings help explain these patterns by showing how dashboard and platform information are used within organisational practice.

The interviews indicate that dashboard information does not become organisationally relevant through access alone. Its role depends on user interpretation, data confidence, fit with organisational routines, clear follow-up responsibility, and the feasibility of action within the wider waste-value ecosystem. These conditions do not operate separately. They interact across user, organisational, and ecosystem levels.

Informational dashboard engagement is reflected in dashboard use for reporting, monitoring, insight, and performance interpretation. Routine transactional engagement appears in operational platform use, such as order placement, collection requests, and document retrieval. Reliance on Milgro, e-mail, telephone contact, interpretation meetings, or advisory support appeared mainly as a way through which users sought clarification, contextual interpretation, or operational support. Non-routine operational engagement appears in incidents, deviations, additional collection needs, and ad hoc problem-solving.

The qualitative analysis therefore does not replace the engagement dimensions used in the quantitative analysis. It explains how these dimensions are enacted and combined within organisations.

9.2. Dashboard and platform use in practice

The interviews show that dashboard and platform use differ substantially between organisations. This supports the quantitative finding that platform engagement is multidimensional rather than a single uniform scale. Organisations do not simply use the platform more or less. They use different parts of the platform for different purposes.

Across the interviews, four dominant forms of use were identified: reporting and accountability, monitoring and control, operational platform use, and selective or ad hoc use. These forms of use relate to the engagement dimensions introduced in Chapter 5 and operationalised in Chapter 6, but they do not map onto them mechanically. Reporting, monitoring, and control mainly reflect informational dashboard engagement. Operational ordering, collection requests, and document retrieval mainly reflect routine transactional engagement. Selective or ad hoc use often overlaps with support-related and non-routine operational engagement.

The most common form of dashboard use was reporting-oriented. Several organisations used dashboard information for monthly or annual reports, KPI reporting, ESG or CSRD-related reporting, ISO documentation, audit preparation, customer reporting, or internal management information. In these organisations, the dashboard provided a structured source of waste-related data that could be used for accountability purposes. One respondent described this use directly: “I mainly use the dashboard reports every month for the KPI reports” (Interviewed organisation 4). Dashboard information was therefore often embedded in reporting cycles before it was embedded in operational decision-making.

A second form of use concerned monitoring and control. Some organisations used dashboard data to follow waste streams, separation percentages, waste-related costs, CO₂-related indicators, or location-level differences. In these cases, the dashboard functioned as a monitoring instrument. It helped users identify deviations, compare trends, or check whether reported waste flows aligned with expectations. However, monitoring did not always lead directly to intervention. In several organisations, dashboard information was used to understand what was happening, but not necessarily to decide what should happen next.

A third form of use was operational platform use. This concerned practical waste-management processes, such as placing collection requests, arranging container changes, retrieving documents, checking orders, or managing operational communication. In some organisations, operational platform use was performed by local facility, logistics, or administrative staff, while dashboard analysis was performed by central sustainability, facility, HSEQ, finance, or reporting staff. One local user described the platform mainly as a practical ordering tool: “Is the container full? I log into the platform, place the order, the container is exchanged or emptied, and then we continue” (Interviewed organisation 14).

This illustrates that platform use and dashboard use are not the same. An organisation may use the platform regularly for operational processes while hardly using the dashboard for performance monitoring. Conversely, dashboard information may be used centrally while local users mainly interact with operational parts of the platform.

A fourth pattern was selective or ad hoc dashboard use. In several organisations, the dashboard was consulted mainly when a question, reporting deadline, customer request, audit requirement, cost deviation, or waste-related incident occurred. In such cases, dashboard use was not absent, but it was not structurally embedded either. The dashboard functioned as a reference source rather than as a recurring steering instrument. One respondent described this separation between central and local use as follows: “The dashboard, I do not use that myself. I think that is really handled centrally” (Interviewed organisation 7).

These findings nuance the meaning of dashboard engagement in the quantitative data. High dashboard engagement may indicate structurally embedded monitoring, but it may also reflect reporting peaks, centralised data work, or repeated consultation by a small number of users. Low dashboard engagement does not necessarily mean that an organisation lacks waste-management routines. It may also mean that monitoring occurs through alternative information sources, direct operational knowledge, or internal systems outside the Milgro dashboard.

9.3. User-level conditions: usefulness, actionability, and data confidence

This section examines the user-level conditions that shape informational dashboard engagement. The interviews show that users often perceive dashboard information as useful, but that usefulness does not automatically imply actionability. Dashboard information becomes more relevant for follow-up when users understand it, trust it, and can connect it to a concrete issue or decision.

9.3.1. Perceived usefulness: insight, visibility, and reporting value

Across the interviews, most respondents perceived the Milgro platform or dashboard as useful. However, the type of usefulness differed between organisations. The dashboard was most consistently valued for three purposes: creating insight into waste streams, improving data visibility and accessibility, and supporting reporting or accountability processes.

First, respondents valued the dashboard because it made waste streams more visible. Several interviewees described the dashboard as a way to obtain an overview of waste volumes, costs, separation performance, CO₂-related indicators, or waste destinations. This was particularly relevant in organisations with multiple locations, departments, or waste streams, where waste information would otherwise be dispersed across invoices, freight documents, internal files, or direct communication with waste-service providers. One respondent emphasised that the dashboard itself was not the limiting factor: “I find it a very useful dashboard. That we use it little is not due to the quality of the dashboard” (Interviewed organisation 9).

Second, perceived usefulness was strongly linked to reporting efficiency. For several organisations, the platform provided a structured data source for ESG reporting, CSRD preparation, ISO documentation, customer reporting, internal management reports, or audit-related questions. In these cases, the dashboard reduced the effort required to retrieve, structure, and justify waste-related data. This reporting value was especially visible where sustainability, ESG, HSEQ, finance, or central service functions were responsible for collecting performance information.

Third, respondents valued the dashboard as a supporting tool for trend monitoring and deviation detection. Some organisations used dashboard information to follow waste-related costs, compare performance over time, or detect unexpected changes in specific waste streams. One respondent described the value of bringing fragmented information together: “By getting those insights in one place, people were shocked by the amount” (Interviewed organisation 8). The dashboard created a starting point for further investigation into possible causes, such as quality problems, pallet flows, or operational processes.

A recurring pattern is therefore that perceived usefulness was often high, but mainly informational or reporting-oriented. Users frequently appreciated the dashboard as a source of overview, transparency, and accountability. This did not automatically mean that the dashboard functioned as a steering instrument. This distinction is important for interpreting high engagement / low performance organisations. In these organisations, dashboard information could be valuable and frequently used, while still being mainly connected to reporting, validation, or central monitoring.

The interviews also show that perceived usefulness depends on organisational role. Central sustainability, ESG, HSEQ, facility, finance, or reporting users often valued the dashboard because it helped them collect and interpret data across organisational units. Local operational users, by contrast, often valued the platform mainly for practical tasks such as placing orders, arranging container changes, or retrieving documents. For them, dashboard information was useful only when it directly supported their immediate responsibilities.

Perceived usefulness was weakest where respondents did not experience a clear fit between the platform and existing routines. Some organisations relied on alternative internal systems, Excel sheets, invoices, freight documents, or direct communication channels because these fitted their operational processes better. In such cases, low dashboard engagement did not necessarily reflect lack of attention to waste management. It reflected that the dashboard was not perceived as the most relevant or efficient information source for that workflow.

Overall, the findings suggest that perceived usefulness is relevant for sustained dashboard use, but insufficient for organisational follow-up. The dashboard is often valued for visibility, insight, and reporting support. Whether these forms of usefulness become practically relevant depends on their connection to routines, ownership, operational control, and follow-up processes.

9.3.2. From insight to action: perceived actionability

The interviews show that dashboard information becomes actionable only under specific conditions. While most respondents recognised the usefulness of dashboard information, fewer described situations in which dashboard insights directly led to operational change, investment decisions, or systematic improvement. This distinction is central to SQ3.

Dashboard information became most actionable when it identified a concrete issue that could be linked to a specific waste stream, cost development, location, or operational process. In such cases, dashboard information did not remain abstract performance feedback. It became a trigger for investigation, discussion, or improvement. One respondent described how increasing costs for a specific residual stream led to an investment discussion: “We saw the costs for almond skins increasing, so we are now looking at an investment to address those costs” (Interviewed organisation 1).

A second actionable pattern appeared when dashboard information was connected to recurring internal follow-up routines. In these organisations, deviations in waste figures, residual waste levels, or specific material streams were not only noticed, but also discussed with departments or operational managers. One respondent described how dashboard information contributed to concrete logistics improvements: “We are now looking at whether we can add a press container for wood, because we notice that we use many containers. We are also testing a trailer at the dock for good pallets, so that they can be reused” (Interviewed organisation 5).

In many cases, dashboard information triggered investigation or discussion rather than immediate action. This is still relevant. Dashboard information could raise questions about why costs increased, why separation performance changed, why a waste stream was classified in a certain way, or why a location deviated from expectations. However, further interpretation was often needed before action could be taken. This was especially the case when dashboard data had to be combined with local process knowledge, operational explanations, or input from Milgro.

The interviews also show that insight often did not translate into action. In several high engagement / low performance organisations, dashboard information was used intensively for reporting, accountability, validation, or awareness creation, but remained weakly connected to operational change. This was particularly visible where dashboard users were not the same actors as those who controlled waste-producing processes. Dashboard information could show that improvement was needed, but the organisation still had to mobilise departments, locations, suppliers, or operational teams to act on that information.

Actionability was also limited when dashboard information was too general, delayed, or disconnected from decision points. Some respondents indicated that dashboard information was useful for longer-term monitoring, but not for short-term steering. Others explained that data could only be interpreted after invoices had been processed, after waste had already been collected, or after figures had been corrected. In these cases, dashboard information supported retrospective understanding, but not necessarily timely intervention.

Overall, dashboard actionability depends on more than data availability. Dashboard information becomes more actionable when it is specific enough to indicate a concrete issue, timely enough to support follow-up, connected to users with relevant responsibilities, and embedded in routines where deviations can be discussed and assigned to action owners. Where these conditions are absent, dashboard information remains mainly informational. It creates insight, awareness, or accountability, but does not directly support circular-performance improvement.

9.3.3. Data limitations and contextual interpretation

The interviews show that data limitations form an important boundary condition for dashboard usefulness and actionability. Respondents did not generally describe the dashboard as irrelevant or unusable, but they did identify several limitations that affected how confidently and quickly dashboard information could be used. These limitations concerned data timeliness, completeness, scope, definitions, granularity, and the need for contextual interpretation.

A first recurring limitation concerned the timing of dashboard data. Several respondents indicated that dashboard information was not always available at the moment it was needed for reporting, decision-making, or operational follow-up. In some organisations, waste data depended on later invoice processing or corrections, meaning that figures could still change after an initial reporting moment. One respondent explained: “For reporting, it is very unfavourable that figures are still changed later” (Interviewed organisation 6). This illustrates how delayed or changing data can reduce confidence, especially when organisations need stable figures for accountability or audit purposes.

A second limitation concerned data completeness and scope. Some respondents noted that not all relevant locations, factories, waste streams, or organisational entities were included in the platform. This was particularly relevant for larger or multi-site organisations, where group-level reporting requires consistent coverage across sites. When the platform covers only part of the organisation, dashboard information can still be useful locally, but its value for strategic or corporate-level decision-making becomes more limited.

Third, several respondents pointed to issues of granularity. Dashboard information was often useful at an aggregate level, but not always detailed enough to support action at the level where waste was generated. An organisation may be able to see total waste volumes, costs, or separation performance, but not always identify the specific department, production line, shop, route, or operational process responsible for a deviation. This limits actionability because improvement measures usually need to be implemented at a more specific operational level.

A fourth limitation concerned definitions and classifications. Waste streams, treatment categories, CO₂ calculations, or internal reporting categories did not always align with how organisations defined circularity, sustainability, or waste performance internally. This created interpretation work for users. Where definitions did not align, dashboard information remained useful as a data source, but required additional processing before it could be used in internal reporting or decision-making. One respondent gave a concrete example: “We asked how much fixer waste we had offered in 2025, and then we were told that it had not been registered separately because it was counted under low-calorific waste. Then I cannot extract that data, because it is simply listed under another waste stream” (Interviewed organisation 6).

These limitations help explain why respondents often emphasised the need for contextual interpretation. Dashboard data rarely spoke for themselves. Users needed knowledge of production processes, logistics routines, healthcare protocols, facility practices, supplier arrangements, or local site conditions to understand what a dashboard figure meant. One respondent summarised this clearly: “You cannot actually steer on the data alone. You also need to know your process well” (Interviewed organisation 13).

Data limitations did not necessarily prevent dashboard use. The platform often remained the best available source for reporting, trend monitoring, or external accountability. However, data limitations affected the type of use. Where data were delayed, incomplete, or too aggregated, dashboard information was more likely to be used for retrospective reporting and discussion than for direct operational steering.

9.4. Organisational conditions: routines, ownership, and follow-up

This section examines organisational conditions that shape whether dashboard information becomes embedded and connected to follow-up. The interviews show that dashboard use becomes more relevant when it is connected to recurring routines, clear responsibilities, and feasible routes for action.

9.4.1. Reporting routines versus operational routines

Organisational embedding emerged as a central condition for sustained platform engagement. Dashboard information became more meaningful when it was connected to recurring routines, such as reporting cycles, management meetings, operational reviews, customer meetings, or action follow-up processes. However, the interviews also revealed an important distinction: dashboard information was often embedded in reporting routines, but less consistently embedded in operational steering routines.

Reporting embeddedness was the most common form of organisational embedding. Several organisations used dashboard information at recurring reporting moments, such as monthly KPI reporting, quarterly reviews, annual sustainability reporting, ESG reporting, CSRD preparation, ISO documentation, customer reporting, or audit-related reporting. In these cases, dashboard use had a clear organisational place. Data were retrieved because a reporting deadline, accountability requirement, or management information need required them. This made dashboard use recurring and purposeful, but not necessarily action-oriented.

In some organisations, reporting routines were closely connected to management or operational follow-up. These organisations showed a stronger link between dashboard information and action. One respondent explained that dashboard information was discussed in recurring management routines: “It comes back in our management meeting, where we monitor it every quarter” (Interviewed organisation 13). In such cases, dashboard information did not only serve as a data source for reporting. It entered a recurring organisational conversation in which performance could be reviewed and interpreted.

The strongest examples of embedded dashboard use were found where dashboard information was connected to follow-up routines. In these organisations, deviations or waste-related trends were discussed with departments, operational managers, or responsible teams. Dashboard information could then lead to action registers, improvement projects, or follow-up questions. This suggests that dashboard information becomes more actionable when it is repeatedly brought into organisational settings where decisions and responsibilities can be assigned.

By contrast, several organisations showed reporting embeddedness without operational embeddedness. In these organisations, dashboard information was used for external accountability, central monitoring, or periodic reporting, but was not structurally discussed in operational meetings or translated into work-floor routines. Dashboard information therefore remained at the level of insight, validation, or reporting. This pattern was particularly visible where sustainability, ESG, finance, or central service functions used the dashboard, while operational teams or local sites were responsible for changing waste practices.

Operational embedding required a closer fit with daily work processes. Operational users often engaged with the platform when they needed to place orders, arrange collections, retrieve documents, or solve practical issues. Strategic or analytical users engaged more strongly with dashboard information for reporting, monitoring, KPI tracking, ESG or CSRD preparation, cost analysis, or performance interpretation. This separation helps explain why platform engagement can appear structurally present while still having limited influence on circular-performance improvement.

In some organisations, dashboard use remained mainly ad hoc. The dashboard was consulted when a specific question, customer request, audit need, invoice issue, or waste-related deviation occurred, but it did not have a fixed place in recurring routines. One respondent described this absence of structured dashboard follow-up clearly: “It is not that we sit down every quarter with the Milgro figures to see where we can improve” (Interviewed organisation 11).

Overall, organisational embedding is a key condition for sustained and actionable dashboard engagement. Dashboard use becomes more meaningful when it is connected to routines that bring together data, interpretation, responsibility, and follow-up. Where dashboard use is embedded only in reporting cycles, it can support transparency and accountability, but its influence on circular-performance improvement remains limited.

9.4.2. Ownership and responsibility: the monitoring-action gap

The interviews show that ownership and responsibility strongly shape whether dashboard information becomes actionable. Responsibility for platform use, dashboard interpretation, and operational follow-up is often distributed across different actors. Even when dashboard information is useful and embedded in reporting routines, it does not automatically lead to follow-up if it is unclear who should interpret the information, who should decide on action, and who should implement changes.

A recurring pattern across the interviews is therefore a monitoring-action gap. The person or department that monitors dashboard information is often not the same actor as the one that can change waste-related practices.

In several organisations, dashboard monitoring was concentrated in central functions, such as sustainability, ESG, HSEQ, facility management, finance, contract management, or a central service organisation. These users were often responsible for collecting data, preparing reports, validating figures, or identifying deviations. However, the ability to change waste practices was located elsewhere: in production departments, local sites, logistics teams, healthcare departments, store operations, suppliers, or external service providers.

Some organisations managed this separation relatively well by creating explicit follow-up routes. In these cases, the dashboard user did not need to control all operational processes personally, because deviations could be assigned to the relevant department or responsible manager. One respondent described this division of responsibility clearly: “I monitor it, but responsibility for taking action lies with the department itself” (Interviewed organisation 4).

In other organisations, the monitoring-action split created a barrier. Dashboard users could identify patterns or reporting issues, but had limited authority to intervene in the operational processes that generated the waste. This was especially visible in larger, decentralised, or professionally fragmented organisations. One respondent explained: “The people who use the platform are not the people who ultimately ensure that less waste is produced or that waste is better separated” (Interviewed organisation 6). In such cases, dashboard information creates visibility, but the route from visibility to operational change remains indirect.

Ownership problems were not limited to large organisations. In smaller organisations, dashboard use and waste follow-up could depend heavily on one individual. This role concentration made engagement vulnerable. When one person had limited time, competing responsibilities, or no formal mandate, dashboard use remained incidental.

Responsibility for different engagement dimensions was also not always aligned with responsibility for circular performance. Operational users may be responsible for routine transactional engagement, such as placing orders or arranging collections. Sustainability or management users may be responsible for informational dashboard engagement, such as reporting and performance interpretation. Facility or logistics teams may manage waste flows, while procurement or suppliers influence packaging and material inputs. This means that the actor who sees a problem in the dashboard may not be the actor who can solve it.

Clear ownership therefore emerged as an enabling condition. Dashboard information was more likely to become actionable when organisations had an identifiable owner for monitoring, a clear route for assigning follow-up, and operational actors who accepted responsibility for improvement. Where ownership was fragmented or unclear, dashboard information was more likely to remain informational, even when users perceived it as useful.

9.4.3. Capacity, priority, and organisational constraints

The interviews also show that sustained dashboard engagement is shaped by practical organisational barriers. These barriers do not necessarily mean that organisations reject the platform or consider dashboard information irrelevant. Rather, they affect whether users have the time, capacity, authority, or organisational priority needed to use dashboard information consistently and translate it into follow-up.

A first recurring barrier was priority. Several respondents indicated that waste management and dashboard use had to compete with other organisational tasks. In some organisations, waste was primarily treated as an operational necessity. It had to be collected, removed, reported, or paid for, but

it was not always a central management topic. This limited the extent to which dashboard information was reviewed proactively. One respondent described this as a fit problem between the platform and internal users: “People think: oh no, another tool, now I have to dive into that again. They do not have enough of a pain point that it solves for them. I had a real pain point, and Milgro solved that” (Interviewed organisation 3).

A second barrier concerned time and capacity. Even when respondents saw the dashboard as useful, they did not always have enough time to analyse figures, investigate deviations, discuss results internally, or follow up on improvement opportunities. This was especially visible where waste monitoring was one of many responsibilities assigned to a facility, HSEQ, sustainability, or operational role. When no dedicated role existed, dashboard use was more likely to remain periodic, reactive, or linked to reporting deadlines.

Third, operational feasibility constrained the translation of dashboard information into action. Dashboard data could reveal a problem, but organisations still needed practical possibilities to respond. Improvement could be limited by physical space for separate containers, production requirements, hygiene or safety rules, transport arrangements, customer requirements, or investment constraints. In such situations, the dashboard helped identify a performance issue, but did not remove the operational constraints that made improvement difficult.

These organisational barriers help explain why useful dashboard information may remain weakly embedded. They also show why similar dashboard engagement can have different meanings across organisations. In one organisation, dashboard use may indicate active steering. In another, it may reflect reporting pressure, ad hoc information retrieval, or centralised data work with limited operational follow-up.

9.5. Ecosystem and external conditions

This section examines ecosystem and external conditions that shape platform engagement and circular-performance follow-up. The interviews show that organisations often depend on actors beyond the dashboard user group, including suppliers, customers, waste processors, transporters, auditors, corporate headquarters, and Milgro itself.

9.5.1. Sector-specific and operational constraints

Sector-specific conditions were important across the interviews. In food-producing organisations, dashboard engagement was shaped by production planning, organic residual streams, food-safety requirements, and the need for rapid waste handling. In healthcare, dashboard use was shaped by medical protocols, hygiene requirements, patient safety, many different waste streams, and complex departmental structures. In logistics, waste-management possibilities were affected by warehouse processes, pallets, container filling, transport efficiency, and customer requirements. In mobility and repair contexts, space constraints, hazardous materials, workshop routines, and decentralised local practices shaped what could realistically be changed.

These examples show that sector conditions shape not only whether organisations use dashboard information, but also whether dashboard insights can realistically be translated into circular-performance improvement. A dashboard indicator may have a different practical meaning in a food factory, a hospital, a logistics warehouse, a repair network, or a public-transport maintenance organisation.

The interviews also show that barriers differ by order-volume-based customer size and organisational complexity. Larger organisations often had more formal reporting needs, more dashboard activity, and more specialised roles. They also experienced greater fragmentation between departments, locations, and responsibilities. Smaller organisations sometimes had fewer formal routines and less capacity for structured dashboard use, but could rely more directly on local process knowledge. This helps explain why customer size in the quantitative analysis was associated more with the consistency and form of engagement than with relative dashboard intensity alone.

9.5.2. External dependencies in the waste-value ecosystem

A first external dependency concerns supply-chain actors. Several organisations explained that waste performance is partly determined upstream by suppliers, packaging choices, incoming materials,

pallets, or customer-specific requirements. In such cases, the dashboard can make a waste stream visible, but the organisation cannot always change the underlying cause independently. Improvement may require coordination with suppliers or customers. One respondent summarised this broader coordination challenge clearly: “You need to get the rest of the chain on board if you want to take steps” (Interviewed organisation 2).

A second dependency concerns waste processors, recyclers, and transporters. Dashboard information may indicate that a waste stream could be separated more effectively, transported more efficiently, or valorised differently. Implementation, however, depends on whether external parties can accept, process, collect, or reuse the material. This was particularly visible in organisations dealing with specialised, hazardous, organic, or sector-specific waste streams.

A third dependency concerns external reporting and accountability pressures. Several organisations used dashboard information because customers, auditors, corporate headquarters, investors, ISO requirements, or CSRD-related processes required waste or sustainability data. These pressures increased the perceived importance of dashboard data and helped embed dashboard use in reporting routines. However, external reporting pressure did not always lead to operational improvement. In several cases, it strengthened the role of the dashboard as an accountability and data-collection tool rather than as a direct steering instrument.

Together, these findings show that dashboard transparency does not equal organisational control. Dashboard information may reveal an improvement opportunity, but the ability to act often depends on suppliers, customers, processors, transporters, internal departments, or regulatory requirements.

9.5.3. Contextual translation of dashboard information

The interviews showed that dashboard information often required contextual translation before it became practically meaningful. Respondents did not always interpret dashboard figures directly from the interface alone. Changes in waste volumes, costs, separation percentages, CO₂-related indicators, or waste-stream classifications needed to be connected to operational processes, sector-specific constraints, organisational priorities, and possible improvement options. In this sense, dashboard data did not speak for themselves.

This issue was particularly visible where dashboard information was not sufficiently sector- or organisation-specific to be independently understood by client organisations. Figures could indicate that something had changed, but they did not always clarify whether this change represented a performance issue, an unavoidable operational circumstance, a classification problem, or a realistic improvement opportunity. As a result, the practical meaning of dashboard information depended on the availability of contextual knowledge about the organisation's waste streams, operational processes, sector requirements, and follow-up possibilities.

In several organisations, this contextual translation was supported by Milgro. Respondents described Milgro as helping to explain dashboard figures, validate waste-stream classifications, identify improvement opportunities, suggest alternative processing routes, or translate data into practical recommendations. One respondent described this role explicitly: “The tool is then used more by Milgro itself, which gives advice based on process knowledge” (Interviewed organisation 3).

This pattern was particularly relevant where client organisations had limited internal time, expertise, or process knowledge to interpret dashboard information themselves. In such cases, Milgro's input helped connect dashboard figures to waste-management expertise and possible follow-up options. One respondent explained that Milgro's expertise helped make a classification issue discussable internally: “That helped, because I was not the only one saying it; the tool said it as well, and these are specialists in that field” (Interviewed organisation 3).

Analytically, this finding highlights contextual interpretation as a socio-technical condition for the practical use of dashboard information. Dashboard data become useful for organisational follow-up when they are connected to the specific sectoral and organisational context in which users operate. This translation may be enabled through internal expertise, embedded organisational routines, platform design, or provider input. The central issue is whether platform information is sufficiently interpretable within the user's operational context to support meaningful interpretation and possible follow-up.

9.6. Cross-profile comparison: explaining engagement-performance contrasts

The thematic findings above show that dashboard usefulness, perceived actionability, organisational embedding, ownership, barriers, and external dependencies differ across organisations. This section brings these findings together by comparing the five engagement-performance profiles used for interview selection. The cross-organisation comparison tables that informed this synthesis are reported in Appendix I.2.

The high engagement / high performance organisations show the clearest link between dashboard information and organisational follow-up. In these organisations, dashboard and platform information were not only used for reporting, but also connected to monitoring routines, management discussions, customer meetings, or operational improvement processes. Dashboard information could trigger investigation, support business cases, or lead to follow-up with departments and operational managers. This does not mean that dashboard use caused stronger performance. It suggests that dashboard engagement was more likely to become meaningful because it was embedded in routines that connected information to action.

The high engagement / low performance organisations show a different pattern. In these organisations, dashboard information was often used intensively and perceived as useful, but mainly for reporting, central monitoring, data validation, external accountability, or awareness creation. The main limitation was not necessarily the dashboard itself, but the organisational translation of dashboard information into action. Monitoring and action were often separated across departments, locations, organisational levels, or professional roles. This helps explain why high dashboard engagement did not necessarily coincide with stronger circular performance. Engagement created visibility, but visibility did not automatically change the practices that generated waste.

The low engagement / high performance profile was represented by one organisation in the realised interview sample. The interview showed that limited use of the Milgro dashboard did not mean that high performance was achieved without information-based steering. Waste monitoring and follow-up were supported by alternative internal information platforms and routines through which follow-up was initiated. The underlying conditions through which waste information was translated into organisational action were similar to the conditions identified in the high engagement / high performance interviews.

The low engagement / low performance organisations showed a more limited engagement pattern. Platform use was mainly operational, reactive, or linked to occasional reporting and external questions. Dashboard information was not strongly embedded in recurring routines, ownership was less clearly organised, and waste improvement had limited priority or capacity. In these organisations, low engagement reflected more than a preference for alternative routines. It indicated that the organisational conditions for sustained platform engagement and continuous improvement were weakly developed.

The mixed / intermediate organisations occupied hybrid positions between these profiles. In some cases, dashboard information was useful for reporting, monitoring, contract control, or specific checks, but was not consistently used for operational steering. In other cases, platform use was embedded for operational tasks, such as order placement, while dashboard access or dashboard-based steering remained limited. These organisations show that engagement-performance relationships are rarely binary. Organisations may use the platform meaningfully for some tasks while leaving other potential uses underdeveloped.

Table 9.1 summarises the main qualitative patterns across the engagement-performance profiles.

Table 9.1: Cross-profile summary of qualitative patterns

Engagement-performance profile	Dominant platform/dashboard role	Main organisational condition	Interpretation
High engagement / High performance	Dashboard and platform information are used for reporting, monitoring, and, in several organisations, improvement projects or operational follow-up.	Dashboard information is more often linked to recurring routines, clearer ownership structures, management attention, and operational follow-up.	Dashboard engagement is more likely to contribute to circular-performance improvement when it is embedded in routines that connect information to action.
High engagement / Low performance	Dashboard information is used intensively, but mainly for reporting, central monitoring, data validation, external accountability, or awareness creation.	Monitoring and action are often separated across departments, locations, organisational levels, or professional roles.	High dashboard engagement creates visibility, but visibility does not automatically translate into circular-performance improvement when action ownership is fragmented or operational control is limited.
Low engagement / High performance	This profile contained only one organisation in the dataset. The interview showed that limited use of the Milgro dashboard did not mean that high performance was achieved without information-based steering. Waste monitoring and follow-up were supported by alternative internal information platforms and routines through which follow-up was initiated.	The underlying conditions through which waste information was translated into organisational action were similar to those identified in the high engagement / high performance interviews, but were organised outside the Milgro dashboard environment.	Low Milgro-dashboard engagement does not necessarily indicate weak information-based steering. It may also reflect that relevant information use and follow-up routines are organised through alternative internal information infrastructures.
Low engagement / Low performance	Platform use remains limited, reactive, operational, or focused on occasional reporting and external questions.	Weak routines, low priority, limited capacity, and unclear ownership constrain sustained platform engagement and follow-up.	Low engagement reflects limited organisational capacity or motivation to translate waste information into continuous improvement.
Mixed/intermediate	Dashboard and platform use are selective: useful for reporting, contract control, specific checks, or operational orders, but not consistently used for steering.	Value depends on task-specific needs, access, process knowledge, perceived relevance, and the fit between dashboard information and operational routines.	Organisations often occupy hybrid positions between reporting-oriented and action-oriented dashboard use.

To further clarify the explanatory role of the qualitative findings, Table 9.2 summarises the main mechanisms through which interview evidence helps explain the quantitative patterns reported in Chapter 7. The mechanisms are not treated as isolated themes, but as explanatory links between observable platform-use patterns and the organisational or ecosystem conditions under which dashboard information becomes connected to organisational follow-up.

Table 9.2: Qualitative mechanisms explaining dashboard engagement and circular-performance patterns

Mechanism	Qualitative evidence	Explains quantitative pattern	Analytical implication
Reporting embeddedness without operational routine embedding	Dashboard information is often used for KPI reporting, ESG or CSRD reporting, ISO documentation, audit preparation, customer reporting, or internal management information, while operational follow-up is less consistently organised.	High dashboard use does not always coincide with high circular performance.	Platform use can be structurally present without being action-oriented. Reporting routines create visibility, but do not necessarily produce operational change.
Monitoring-action gap	Dashboard monitoring is often concentrated in central sustainability, ESG, HSEQ, finance, facility, or service roles, while the ability to change waste-producing practices lies with departments, locations, suppliers, or operational teams.	Informational dashboard use may create awareness without corresponding performance improvement.	Ownership and follow-up responsibility appear important for dashboard information to become connected to organisational follow-up.
Contextual interpretation requirement	Dashboard figures often require operational, organisational, and sector-specific context before they can be interpreted correctly. Changes in waste volume, costs, separation percentages, CO ₂ -related indicators, or waste-stream classifications do not speak for themselves. In several organisations, especially where internal time, expertise, or process knowledge was limited, Milgro helped translate dashboard figures into practical recommendations, improvement opportunities, or possible follow-up actions.	Dashboard views per 100 orders are not robustly associated with circular-performance indicators. Dashboard use may remain informational when users cannot independently interpret what figures mean or what action they imply.	Data visibility alone is insufficient. Dashboard information becomes meaningful only when it is sufficiently sector- and organisation-specific, or when it is translated into the relevant organisational and operational context. This translation may be supported by internal expertise, embedded routines, platform design, or provider input, but analytically it concerns the interpretability and practical meaning of the data.
Data-confidence concerns	Some users hesitated to rely fully on dashboard data because of questions about timeliness, completeness, classification, consistency, or alignment with internal definitions. Where users doubted the data, the dashboard was less likely to be used as a basis for decisions or follow-up.	Dashboard engagement does not necessarily coincide with performance improvement when users do not fully trust the underlying data.	Data reliability and perceived credibility shape whether dashboard information can become a basis for interpretation, discussion, and follow-up.
Alternative information infrastructure outside the Milgro platform	The interview showed that limited use of the Milgro dashboard did not mean that high performance was achieved without information-based steering. Waste monitoring and follow-up were supported by alternative internal information platforms and routines through which follow-up was initiated.	Low Milgro-dashboard engagement can coincide with high performance when the relevant information infrastructure lies outside the focal platform. In this case, the conditions for translating waste information into action resembled those found in the high engagement / high performance interviews.	The quantitative engagement indicators capture engagement with the Milgro platform, not the full range of information systems through which organisations may steer waste performance. Low platform engagement should therefore not be interpreted as absence of information-based monitoring, interpretation, or follow-up capacity.
Operational platform use separated from dashboard use	Some organisations use the platform mainly for practical waste-management tasks, such as placing collection requests, arranging container changes, retrieving documents, checking orders, or managing communication. These operational users do not necessarily use the dashboard for performance interpretation.	Platform use and dashboard use do not consistently move together. Organisations may be operationally active on the platform without using dashboard information as a steering instrument.	Platform engagement is multidimensional. Different platform functions support different organisational purposes and should not be collapsed into one general measure of use.
Ecosystem-constrained follow-up	Improvement opportunities often depend on suppliers, customers, processors, transporters, regulatory requirements, contractual arrangements, collection logistics, or sector-specific constraints such as hygiene, safety, space, or production requirements.	Associations between dashboard use and performance weaken after sector and customer-size controls are included.	Circular-performance improvement depends partly on ecosystem-level feasibility. Transparency does not necessarily imply organisational control or operational follow-up.
Structural activity as routine signal	Regular dashboard activity more often reflects recurring reporting, monitoring, management attention, or repeated performance review, while high dashboard intensity can reflect ad hoc checks, reporting peaks, or data validation.	Structural dashboard activity is more meaningfully associated with circular-performance indicators than raw dashboard intensity.	Recurring and embedded use is more informative than isolated viewing intensity, but its organisational meaning still depends on whether dashboard information is interpreted, discussed, and followed up in practice.

Across the profiles and mechanisms, one overarching pattern emerges. Informational dashboard engagement becomes more likely to support circular-performance improvement when users perceive the information as useful and trustworthy, when the information can be interpreted in context, when dashboard use is embedded in routines, when ownership for follow-up is clear, and when action is feasible within the wider organisational and ecosystem context. Where these conditions are weak, dashboard engagement remains mainly informational, report-oriented, or dependent on ad hoc interpretation and non-routine forms of engagement.

This cross-profile comparison helps explain the selective associations found in SQ2. Structural dashboard activity was more clearly associated with circular-performance indicators than dashboard intensity, but the interviews show that structural dashboard activity can have different meanings. It may reflect embedded monitoring, reporting pressure, centralised data work, or ad hoc information retrieval. The qualitative findings therefore clarify why the quantitative relationship between dashboard engagement and circular performance is limited and context-dependent.

Together, Tables 9.1 and 9.2 show how the qualitative findings explain the selective and context-dependent relationship between dashboard use and circular-performance indicators. Section 9.7 synthesises these insights and prepares the integrated discussion in Chapter 10.

9.7. Qualitative synthesis and link to integrated discussion

The qualitative findings provide explanatory depth for SQ3 and SQ4. For SQ3, the interviews show that organisational users generally perceive the Milgro dashboard as useful for visibility, reporting, monitoring, and accountability. However, perceived usefulness does not automatically imply actionability. Dashboard information becomes more actionable when it is specific, timely, trusted, contextually interpreted, and connected to users or routines that can support follow-up.

For SQ4, the interviews show that the translation of platform information into organisational follow-up is shaped by organisational and external conditions. At the organisational level, routines, role allocation, ownership, capacity, and management attention affect whether dashboard information is discussed and followed up. At the ecosystem level, sector-specific constraints, external reporting requirements, supply-chain dependencies, waste-processing options, and the availability of relevant contextual expertise shape whether follow-up is feasible.

Taken together, the findings suggest that platform engagement is not only a matter of use frequency or dashboard intensity. It is a situated organisational practice. Waste-related dashboard information can support circular-performance improvement when it is translated into organisational follow-up, but this translation depends on conditions across user, organisational, and ecosystem levels.

These findings prepare the integrated discussion in Chapter 10. The next chapter brings together the quantitative and qualitative results, answers the main research question, and refines the literature-based analytical framework.

10 | Integrated Discussion and Conclusion

This chapter integrates the quantitative and qualitative findings of the thesis. Chapter 7 showed that engagement with the Milgro platform is uneven, multidimensional, and context-dependent. It also showed that informational dashboard engagement is only selectively associated with circular-performance indicators. Chapter 9 then explained these patterns by showing how dashboard and platform information are interpreted, embedded, and acted upon in organisational practice.

The purpose of this chapter is to bring these findings together and to answer the research question. This chapter first answers the four sub-questions. It then uses these answers to refine the literature-based analytical framework developed in Chapter 4. This refinement leads to the *actionable engagement mechanism*, which specifies the socio-technical conditions under which platform information can be translated into organisational follow-up for circular-performance improvement. This chapter then answers the main research question and discusses the theoretical contribution, practical implications, limitations, and directions for future research.

10.1. Answering the sub-questions

The four sub-questions provide the empirical building blocks for answering the main research question. SQ1 and SQ2 describe the quantitative patterns of platform engagement and dashboard-performance associations. SQ3 and SQ4 explain how these patterns are shaped by user perceptions, organisational routines, responsibility structures, and ecosystem conditions.

10.1.1. SQ1: Variation in platform engagement

SQ1 asked:

How does the use of the digital circular-economy platform vary across organisations?

The quantitative findings show that organisational engagement with the Milgro platform varies substantially across organisations. Engagement is uneven because dashboard use is concentrated among a limited subset of intensive users, while many organisations show low to moderate dashboard activity. This means that access to dashboard functionality does not result in uniform informational dashboard engagement.

The findings also show that engagement is multidimensional. Organisations do not simply score high or low on one general platform-use scale. Instead, they differ across informational dashboard engagement, routine transactional engagement, support-related engagement, and non-routine operational engagement. Some organisations are relatively dashboard-oriented, others are more support-intensive, and others mainly stand out through non-routine operational interactions. High engagement in one dimension therefore does not necessarily imply high engagement in another.

Finally, engagement is context-dependent. Sector and order-volume-based customer size are associated with differences in engagement patterns. Sector differences were visible across multiple engagement indicators, including dashboard views, support intensity, routine channel use, and non-routine operational interactions. Customer size was associated more strongly with the consistency and form of engagement than with relative dashboard intensity alone.

SQ1 therefore shows that platform engagement should not be treated as a single usage measure. It is better understood as a set of different platform interactions that vary in intensity, form, and organisational context.

10.1.2. SQ2: Dashboard engagement and circular-performance indicators

SQ2 asked:

How is the use of performance dashboards associated with available circular-performance indicators?

The quantitative findings show that informational dashboard engagement is associated with circular-performance indicators only selectively. Relative dashboard intensity, measured as dashboard views per 100 orders, was not significantly associated with waste separation percentage, waste-related costs per kilogram, or CO₂-equivalent emissions per kilogram after correction for multiple testing.

Structural dashboard activity showed clearer bivariate associations. Organisations that were active in the dashboard in a larger share of quarters tended to have higher waste separation percentages and lower waste-related costs per kilogram. However, these associations weakened when customer size and sector were included as contextual controls. No clear association was found between structural dashboard activity and CO₂-equivalent emissions per kilogram.

SQ2 therefore suggests that the consistency of dashboard use is more informative than the number of dashboard views alone. At the same time, these associations remain limited and should not be interpreted causally. Dashboard engagement may be related to circular performance, but its meaning depends on broader organisational and contextual conditions.

10.1.3. SQ3: User perceptions of usefulness, relevance, and actionability

SQ3 asked:

How do organisational users understand, interpret, and evaluate dashboard information?

The qualitative findings show that organisational users generally perceive the Milgro dashboard as useful, especially for visibility, reporting, monitoring, and accountability. The dashboard helps bring waste-related information together and makes waste streams, costs, separation performance, and environmental indicators more visible.

However, perceived usefulness did not automatically imply actionability. Dashboard information was most actionable when it pointed to a concrete issue, such as a specific cost increase, waste stream, location, or operational process. It was less actionable when the information was too aggregated, delayed, incomplete, or disconnected from decision points.

The interviews also showed that dashboard data required contextual interpretation. Users needed operational knowledge to understand whether changes in waste volume, costs, separation percentage, or emissions reflected a real performance issue, a temporary event, a classification issue, or a sector-specific constraint. Without such interpretation, dashboard information remained useful as a source of visibility, but less capable of supporting follow-up.

SQ3 therefore shows that users often value platform information, but that value only becomes actionable when the information is trusted, understood, and connected to a possible follow-up decision.

10.1.4. SQ4: Organisational and external conditions shaping sustained engagement

SQ4 asked:

Which organisational and ecosystem-level conditions facilitate or hinder the use of platform information for organisational follow-up within a business-to-business waste-value ecosystem?

The qualitative findings show that the translation of platform information into organisational follow-up is shaped by organisational routines, role allocation, ownership, capacity, priority, and operational feasibility. Dashboard information was often embedded in reporting routines, such as ESG reporting, KPI reporting, audit preparation, or internal management information. This created visibility and accountability. However, reporting embeddedness did not always lead to operational embeddedness.

A central barrier was the monitoring-action gap. The actors who monitored dashboard information were often not the same actors who could change waste-producing practices. Dashboard information

became more actionable when organisations had clear follow-up routes, identifiable owners, and operational actors who could act on the information. Where responsibility was fragmented or unclear, dashboard information often remained informational or report-oriented.

External and ecosystem conditions also shaped whether platform information could be translated into follow-up. Sector-specific constraints, supplier relationships, waste-processing options, transport arrangements, reporting requirements, and the availability of relevant contextual expertise influenced whether organisations could act on platform information. In several organisations, dashboard figures required additional sectoral or operational interpretation before they could be translated into practical follow-up.

SQ4 therefore shows that sustained platform engagement depends on both internal organisational conditions and external ecosystem conditions. Platform information becomes more actionable when routines, responsibilities, and ecosystem feasibility are aligned.

10.2. From literature-based framework to empirical refinement

The answers to the sub-questions refine the literature-based analytical framework developed in Chapter 4. The original framework treated organisational platform engagement as multidimensional and multi-level. It distinguished between different forms of platform engagement and between user-level, organisational-level, and ecosystem-level socio-technical conditions.

The empirical findings support this structure, but they also specify how these conditions operate in the context of a digital circular-economy platform in a business-to-business waste-value ecosystem. The contribution of this thesis therefore lies in empirically refining the literature-based building blocks.

This refinement is important because the literature-based framework was derived from several adjacent literature streams rather than from a mature body of research on the specific technology examined in this thesis. Digital circular-economy platforms in business-to-business waste-value ecosystems combine characteristics of information systems, platform ecosystems, waste-management infrastructures, and circular-economy coordination tools. The empirical study therefore specifies how literature-based socio-technical building blocks need to be interpreted in this specific context.

The literature identified broad socio-technical building blocks at different levels. At the micro level, technology-adoption literature informed the user conditions, including trust, perceived usefulness, relevance, and interpretability. At the meso level, socio-technical and practice-based information-systems literature informed the organisational conditions, including routines, role structures, responsibility, decision-making, and organisational embedding. At the macro level, digital-circularity literature informed the ecosystem and institutional conditions, including ecosystem dependencies, inter-organisational coordination, data conditions, and regulatory context.

The empirical study specifies how these building blocks need to be interpreted for the digital platform technology studied in this thesis. In this context, the key contribution is the identification of several translation gaps: a data-confidence gap, an interpretation gap, a reporting-action gap, a monitoring-action gap, and an ecosystem-feasibility gap.

These gaps explain why platform information does not automatically become circular-performance improvement. Data may be visible but not trusted. Information may be useful but not actionable. Dashboard use may be embedded in reporting but disconnected from operational improvement. Monitoring may be centralised while action depends on departments, sites, suppliers, or operational teams. Improvement may be desirable but infeasible because of external dependencies.

The refined framework therefore specifies the socio-technical conditions that mitigate these gaps. It shows how the literature-based building blocks must be operationally interpreted if platform information is to become relevant for organisational action and circular-performance improvement. In this sense, the refined framework is context-specific: it identifies the conditions under which information from a digital circular-economy platform can become actionable in a B2B waste-value context.

Table 10.1 shows how the literature-based building blocks from Chapter 4 are empirically refined through the translation gaps identified in the Milgro case.

Table 10.1: Refinement from literature-based analytical framework to actionable engagement mechanism

Literature-based building block	Empirical gap identified in the Milgro case	Refined condition	socio-technical	Role in translating information into circular-performance improvement
Trust and data reliability	Data-confidence gap: users may access dashboard information but hesitate to rely on it because data are delayed, incomplete, changing, unclear, insufficiently granular, or not fully aligned with internal definitions.	Data confidence: dashboard data must be sufficiently reliable, timely, complete, understandable, and aligned with organisational definitions and reporting needs.		Ensures that dashboard information can function as a valid basis for interpretation, discussion, reporting, decision-making, and follow-up.
Usefulness, relevance, and interpretability	Interpretation gap: dashboard figures rarely explain themselves and may be misread or remain underused without operational, organisational, and sector-specific context.	Contextual interpretation: dashboard information must be interpreted in relation to waste streams, operational processes, sector constraints, organisational circumstances, and relevant performance expectations.		Turns data visibility into meaningful diagnosis by clarifying what the information indicates and whether it points to a performance issue, contextual circumstance, or improvement opportunity.
Organisational routines and embedding	Reporting-action gap: dashboard information may be embedded in ESG, KPI, audit, CSRD, or management reporting, while remaining disconnected from operational improvement.	Operational routine embedding: dashboard information must enter recurring management, operational review, site-level, or improvement routines in which deviations can be discussed and follow-up can be considered.		Moves dashboard use beyond reporting and creates repeated organisational moments where information can be connected to decisions, priorities, and improvement actions.
Role allocation and responsibility	Monitoring-action gap: the actor who monitors dashboard information is often not the actor who can change waste-producing practices or implement operational improvements. the actor who monitors dashboard information is often not the actor who can change waste-producing practices or implement operational improvements.	Connected ownership and responsibility: responsibility must be assigned for monitoring, interpretation, decision-making, escalation, and implementation of follow-up actions.		Connects information visibility to actors with authority, mandate, process knowledge, or operational influence, thereby increasing the likelihood that insights lead to action.
Ecosystem coordination and institutional context	Ecosystem-feasibility gap: improvement may depend on suppliers, processors, transporters, customers, internal departments, regulatory requirements, contractual arrangements, processing options, or available revalorisation routes.	Feasible ecosystem-level follow-up: improvement options must be practically possible within the wider waste-value ecosystem, including supply-chain, processing, regulatory, contractual, and service relationships.		Ensures that organisational action is not blocked by external dependencies, sector-specific constraints, or missing ecosystem-level possibilities for follow-up.

Table 10.1 connects the literature-based analytical framework to the actionable engagement mechanism developed in this chapter. The refinement consists of five socio-technical conditions: data confidence, contextual interpretation, operational routine embedding, connected ownership and follow-up responsibility, and feasible ecosystem-level follow-up. Together, these conditions specify how waste-related platform information can move beyond visibility and become connected to organisational action for circular-performance improvement.

Table 10.2 complements the framework refinement by showing how the main quantitative patterns are explained by the qualitative findings and how this integration informs the actionable engagement mechanism.

Table 10.2: Integration of quantitative patterns, qualitative explanations, and implications for actionable engagement.

Quantitative pattern	Qualitative explanation	Implication for actionable engagement
Platform engagement is uneven and right-skewed.	Organisations differ in perceived relevance, role allocation, organisational routines, managerial attention, operational capacity, and the extent to which platform information fits their work processes.	Platform access does not produce uniform use. Actionable engagement depends on whether platform information is perceived as relevant, trusted, embedded in routines, and connected to possible follow-up.
Engagement indicators do not move together consistently.	Organisations use dashboards, ordering channels, support interactions, and non-routine channels for different purposes. Dashboard use may reflect reporting or monitoring, while other platform interactions may reflect operational coordination or service needs.	Platform engagement is multidimensional and should not be reduced to one aggregate usage indicator. Different forms of platform use have different relevance for organisational action.
Dashboard views per 100 orders are not robustly associated with circular-performance indicators.	High dashboard-viewing intensity may reflect reporting peaks, ad hoc checks, repeated validation, central monitoring, or information searching without direct operational follow-up.	Engagement intensity is not the same as actionable engagement. Frequent dashboard viewing only becomes relevant for circular-performance improvement when information is interpreted, embedded, assigned, and followed up.
Structural dashboard activity is more meaningfully associated with separation percentage and waste-related costs in the bivariate analysis.	Regular dashboard activity more often reflects recurring monitoring, reporting cycles, management routines, or repeated attention to waste-performance information.	Consistent dashboard activity is more informative than isolated viewing intensity, but it remains insufficient unless connected to operational routines and follow-up responsibility.
Associations weaken after adding sector and customer-size controls.	Sector-specific waste processes, organisational scale, waste-stream composition, operational constraints, and external dependencies affect both platform engagement and circular-performance indicators.	Dashboard information operates through socio-technical context rather than as an independent driver of performance. Sector and organisational conditions shape whether information can become actionable.
High engagement / low performance profiles occur.	Dashboard information may be used intensively for reporting, accountability, validation, or awareness creation while action ownership remains fragmented or operational change depends on actors outside the dashboard user's control.	Transparency does not necessarily imply organisational control or operational improvement. Actionable engagement requires connected ownership and follow-up responsibility.
Low engagement / high performance profiles occur.	The interviewed organisation in this profile showed that limited use of the Milgro dashboard did not mean that waste performance was not information-based. Waste monitoring and follow-up were supported by alternative internal information platforms and embedded routines.	Information contributes when it is connected to existing organisational and operational practices.
Dashboard information is often useful for reporting but less directly for operational steering.	Reporting routines create visibility and accountability, but they do not automatically create moments where deviations are discussed, decisions are made, or actions are assigned.	Reporting embeddedness must be distinguished from operational routine embedding. Platform information becomes more actionable when it enters recurring operational or improvement routines.
Similar dashboard-use patterns can coincide with different performance outcomes.	Organisations differ in data confidence, contextual interpretation, internal ownership, operational authority, and feasibility of follow-up within the wider waste-value ecosystem.	The same observable platform behaviour can have different meanings across organisations. Actionable engagement depends on the combination of the five socio-technical conditions rather than on dashboard use alone.
Platform information can identify potential improvement opportunities, but follow-up is not always within the client organisation's direct control.	Improvement may depend on waste collectors, processors, suppliers, customers, internal departments, contractual arrangements, regulatory constraints, or available revalorisation options.	Circular-performance improvement requires feasible ecosystem-level follow-up. Platform information can support action only when realistic options exist within the wider waste-value ecosystem.

10.3. The actionable engagement mechanism

Building on the integrated findings, this thesis introduces the actionable engagement mechanism as the refined explanation of how waste-related platform information may become connected to organisational action in a B2B waste-value ecosystem. The mechanism specifies how platform information becomes actionable in circular waste management, where information concerns residual material flows, operational change depends on waste-producing practices, and circular follow-up is often shaped by collectors, processors, contracts, regulation, and available revalorisation routes.

The concept of actionable engagement refers to a form of organisational platform engagement in which waste-related platform information is not only accessed or viewed, but also trusted, interpreted, embedded in organisational routines, assigned to responsible actors, and connected to feasible follow-up and improvement.

The actionable engagement mechanism explains the socio-technical conversion of platform information into organisational follow-up. It specifies the conditions under which platform information becomes

more likely to support monitoring, decision-making, operational change, and circular-performance improvement.

The mechanism consists of five socio-technical conditions.

First, **data confidence** is required. Users need to perceive dashboard information as sufficiently reliable, timely, complete, and understandable. If figures change after reporting moments, if waste streams are classified in unexpected ways, or if definitions do not align with internal reporting categories, users may still consult the dashboard, but they are less likely to use it as a basis for action.

Second, **contextual interpretation** is required. Dashboard information becomes meaningful only when users can interpret it in relation to operational processes and waste practices. A change in waste volume, separation percentage, cost per kilogram, or CO₂-equivalent emissions may indicate an improvement opportunity, but it may also reflect a temporary project, production change, waste classification issue, or sector-specific constraint. Contextual interpretation mitigates the risk that dashboard figures remain visible but not understood.

Third, **operational routine embedding** is required. The findings show that dashboard information is often embedded in reporting routines, such as ESG reporting, KPI reporting, audits, CSRD preparation, or internal management information. These routines create visibility and accountability. However, reporting embeddedness does not by itself secure circular-performance improvement. Information becomes more actionable when it is also embedded in operational routines, management reviews, improvement meetings, or recurring follow-up processes where decisions can be made.

Fourth, **connected ownership and follow-up responsibility** are required. The interviews showed a recurring monitoring-action gap: dashboard information is often monitored by central sustainability, HSEQ, facility, finance, or reporting actors, while operational change depends on departments, sites, suppliers, production teams, or local managers. This gap can be mitigated when organisations clarify who monitors the information, who interprets it, who decides on follow-up, and who implements changes.

Fifth, **feasible ecosystem-level follow-up** is required. Circular-performance improvement often depends on actors and constraints beyond the dashboard user. External actors, regulatory requirements, sector-specific constraints, available processing options, and service relationships can all shape whether action is possible. Dashboard transparency therefore does not equal organisational control. Follow-up must be feasible within the wider waste-value ecosystem.

Figure 10.1 visualises the refined mechanism. The figure shows how literature-based socio-technical building blocks at micro, meso, and macro level are empirically refined through the Milgro case study. The empirical findings specify the translation gaps that may prevent platform information from becoming organisationally actionable. These gaps are translated into refined socio-technical conditions for actionable engagement in a digital circular-economy platform in a B2B waste-value ecosystem.

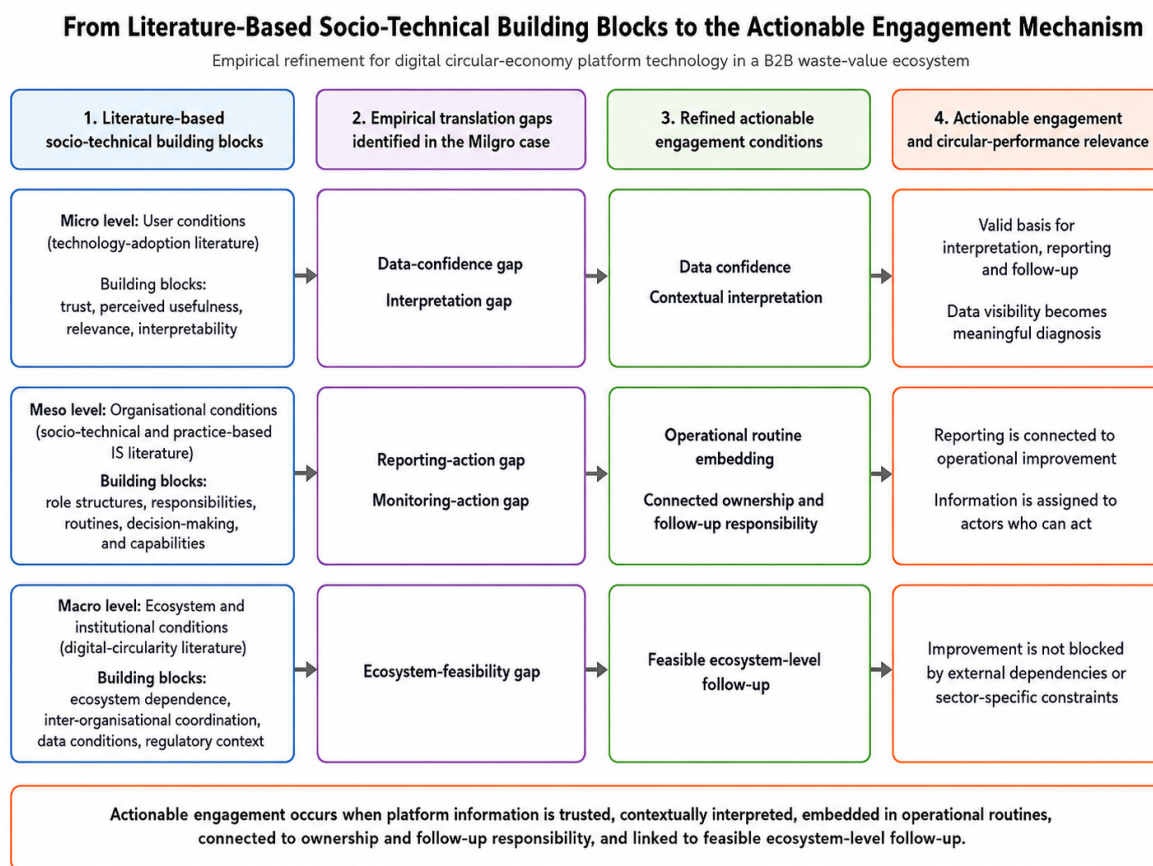


Figure 10.1: From literature-based socio-technical building blocks to the actionable engagement mechanism.

The figure shows how literature-based socio-technical building blocks are empirically refined through observed translation gaps into actionable engagement conditions. The arrows indicate analytical refinement and conversion conditions, not a deterministic causal chain.

The actionable engagement mechanism clarifies why dashboard transparency alone is insufficient. Dashboard views, digital orders, support interactions, and incident reports show that an organisation interacts with the platform. They do not show whether platform information is trusted, interpreted, embedded, assigned, or acted upon. The mechanism therefore connects behavioural engagement with interpretive and organisational conditions.

This mechanism also explains why structural dashboard activity was more informative than relative dashboard intensity in the quantitative analysis. Structural dashboard activity may indicate that dashboard use is more consistently present in organisational routines. However, even structural activity is not sufficient on its own. It becomes performance-relevant only when supported by data confidence, contextual interpretation, operational embedding, ownership, and feasible follow-up.

The broader implication is that digital circular-economy platforms can contribute to circular-economy objectives only when the information they provide is converted into organisational practice. The platform can make waste flows, costs, and environmental indicators visible, but the circular-economy contribution depends on whether organisations can use this information to identify, discuss, assign, and implement improvement opportunities. The actionable engagement mechanism therefore specifies the socio-technical conditions under which digital circular-economy platform technology may contribute to its intended purpose.

10.4. Answer to the main research question

The main research question of this thesis is:

Under which socio-technical conditions can information within a digital circular-economy platform support organisational action for circular-performance improvement in a business-to-business waste-value ecosystem?

The answer follows from the integration of the four sub-questions and the refined actionable engagement mechanism. Information within a digital circular-economy platform can support organisational action for circular-performance improvement when platform engagement is converted into actionable engagement. This conversion is supported by socio-technical conditions that mitigate the empirically identified translation gaps between information visibility and circular-performance improvement.

First, information must be supported by **data confidence**. Users need sufficient confidence in the timing, completeness, definitions, and reliability of dashboard data. This condition mitigates the data-confidence gap. Without data confidence, dashboard information may still support visibility or reporting, but it is unlikely to function as a stable basis for action.

Second, information must be **contextually interpreted**. Waste-related indicators only become meaningful when they are linked to operational processes, waste-stream characteristics, sector-specific constraints, and organisational circumstances. This condition mitigates the interpretation gap. It helps users distinguish between a genuine improvement opportunity and a pattern caused by temporary, technical, or contextual factors.

Third, information must be embedded in **operational routines**, not only in reporting routines. Reporting routines create visibility and accountability, but they do not automatically generate improvement. Platform information becomes more likely to support circular-performance improvement when it enters recurring management, operational review, or improvement routines where deviations are discussed and follow-up can be assigned. This condition mitigates the reporting-action gap.

Fourth, monitoring must be connected to **ownership and responsibility for follow-up**. The monitoring-action gap must be mitigated by clarifying who monitors dashboard information, who interprets it, who has authority to decide on action, and who is responsible for implementation. Without this connection, dashboard information may create awareness without changing waste-producing practices.

Fifth, follow-up must be **feasible within the wider ecosystem**. Circular-performance improvement often requires coordination with suppliers, customers, processors, transporters, internal departments, regulators, or the platform provider. This condition mitigates the ecosystem-feasibility gap. Platform information can support action only when organisations have realistic options to act on the insights produced by the platform.

The answer to the main research question is therefore that information within a digital circular-economy platform supports organisational action for circular-performance improvement when it is trusted, contextually interpreted, embedded in operational routines, connected to clear ownership and follow-up responsibility and linked to feasible action within the wider waste-value ecosystem.

This answer explains why dashboard transparency alone is insufficient. Platform information may be visible but not trusted, useful but not actionable, embedded in reporting but not in operations, monitored centrally but not owned locally, or relevant but infeasible because of external dependencies. Circular-performance improvement is therefore not secured by digital access, dashboard availability, or dashboard intensity alone. It depends on the socio-technical conditions through which information is converted into actionable organisational follow-up.

These conditions also relate to the broader purpose of digital circular-economy platforms. Such platforms are intended to make waste-related information visible, support coordination, and enable organisations to improve circular performance. The findings suggest that this contribution depends on whether platform information becomes actionable in organisational practice. In that sense, safeguarding the refined socio-technical conditions identified in this thesis can support the broader

circular-economy ambition of these platforms, although the study does not claim to prove long-term circular transition effects.

10.5. Theoretical contribution

This thesis makes a specific theoretical contribution by refining the literature-based analytical framework developed in Chapter 4 for the context of digital circular-economy platform technology in a business-to-business waste-value ecosystem. The framework was built from adjacent literature streams, including technology-adoption literature, socio-technical and practice-based information-systems literature, and digital-circularity literature. The empirical findings specify how these general building blocks operate in the specific platform context studied in this thesis.

Table 10.3: Contribution of the thesis in relation to the literature-based analytical framework

Literature stream	Existing literature emphasises	This thesis adds/specifies
Digital circular-economy platform literature	Digital platforms may enable transparency, coordination, data exchange, and circular value creation across ecosystems.	Transparency becomes practically relevant only when platform information is converted into actionable engagement through data confidence, interpretation, routines, ownership, and feasible follow-up.
Technology-adoption literature	User perceptions, such as perceived usefulness, ease of use, trust, and social influence, shape individual technology use.	Technology-adoption concepts are treated as user-level conditions within a broader socio-technical framework. The thesis specifies that perceived usefulness is relevant but insufficient: users may value dashboard information for visibility or reporting, while organisational follow-up still depends on interpretation, routines, ownership, and feasible action.
Socio-technical and practice-based information-systems literature	Technology use becomes meaningful through situated routines, roles, responsibilities, and organisational practices.	The thesis distinguishes reporting embeddedness from operational routine embedding, showing why repeated dashboard use does not automatically imply organisational action.
Dashboard and performance-information literature	Performance data can support monitoring, feedback, learning, and decision-making.	Structural dashboard activity is more meaningful than raw dashboard intensity, but only when connected to interpretation, ownership, and follow-up routines.
Digital-circularity barriers literature	Barriers exist across user, organisational, ecosystem, and institutional levels.	The thesis shows how micro-level perceptions, meso-level routines, and macro-level ecosystem dependencies interact through specific translation gaps.

First, the thesis clarifies how technology-adoption concepts can be used in an organisational platform context. The technology-adoption literature, including concepts commonly associated with TAM, informed the micro-level building blocks of the analytical framework, such as perceived usefulness, trust, relevance, and interpretability. These concepts are originally concerned with individual acceptance and use of technology. Nevertheless, individual users still shape how the technology is enacted in practice. They may decide whether they actively consult the dashboard, whether they rely on dashboard information for reporting or decision-making, whether they use the platform directly for operational tasks, or whether they use alternative channels such as e-mail or telephone contact with Milgro. For example, a user may place a waste order digitally through the platform, but may also choose to contact the helpdesk by telephone. Similarly, a user may have access to dashboard information, but may decide to use it only for reporting, not for operational follow-up. In this way, individual-level perceptions remain relevant, not as a complete explanation of organisational adoption, but as part of the broader socio-technical process through which platform information becomes used, trusted, and interpreted.

The empirical findings refine this micro-level component. Users often perceived the dashboard as useful for visibility, monitoring, and reporting. However, perceived usefulness did not automatically make platform information actionable. The findings show that usefulness needs to be understood together with data confidence and contextual interpretation. In this platform context, the question is therefore not only whether users accept or value the technology, but whether they trust and interpret the information sufficiently to use it as a basis for organisational follow-up.

Second, the thesis contributes to socio-technical and practice-based information-systems literature by specifying how organisational embedding shapes the use of platform information. The literature-based framework identified routines, role structures, responsibility, decision-making, and organisational embedding as meso-level building blocks. The empirical findings refine these concepts by distinguishing between reporting embeddedness and operational routine embedding. Dashboard information may be structurally used for ESG reporting, KPI reporting, audit preparation, or CSRD-related data collection, while still remaining weakly connected to operational improvement routines. This distinction helps explain why repeated platform use does not necessarily imply organisational action.

The findings also specify the importance of the monitoring-action gap. In several organisations, the actor who monitored dashboard information was not the actor who could change waste-producing practices. This shows that organisational embedding requires more than repeated access to information. Platform information becomes more likely to support action when monitoring is connected to ownership, mandate, decision-making, and implementation capacity.

Third, the thesis contributes to digital-circularity and circular-economy platform literature by clarifying the conditions under which platform-enabled transparency may become relevant for circular-performance improvement. Digital circular-economy platforms are often expected to support transparency, coordination, data exchange, and circular decision-making. The findings of this thesis show that transparency is only a starting point. In a B2B waste-value ecosystem, platform information becomes relevant for circular-performance improvement only when it is trusted, contextually interpreted, embedded in operational routines, connected to ownership and follow-up responsibility, and linked to feasible ecosystem-level action.

The main theoretical contribution is therefore the actionable engagement mechanism. This mechanism is a context-specific refinement of the literature-based analytical framework. It connects the empirical translation gaps identified in the study, including the data-confidence gap, interpretation gap, reporting-action gap, monitoring-action gap, and ecosystem-feasibility gap, to refined socio-technical conditions for actionable engagement. The mechanism explains how general socio-technical building blocks need to be specified for digital circular-economy platforms in a B2B waste-value context.

10.6. Practical and societal implications

The practical and societal relevance of this thesis lies in the question of how digital circular-economy platforms can support the broader transition towards a circular economy. The findings show that such platforms do not contribute to circular-performance improvement through data visibility alone. Their contribution depends on whether waste-related information becomes actionable in organisational and ecosystem practice. The practical implications therefore follow directly from the actionable engagement mechanism and focus on the key actors that can help safeguard these conditions.

For platform providers, the findings suggest that dashboards should be designed not only for monitoring and reporting, but also for waste-specific interpretation and action. A dashboard that only presents waste volumes, separation percentages, costs, or CO₂-related indicators may increase visibility, but it does not necessarily help users understand what a deviation means or what kind of follow-up may be possible. Platform providers can therefore increase the practical value of dashboards by designing functionality that reduces the data-confidence and interpretation gaps identified in this thesis.

First, platform providers can strengthen data confidence by making indicator definitions, data sources, update status, and classification logic more transparent. For example, dashboards could distinguish between preliminary and validated figures, indicate when data were last updated, explain whether figures are based on invoices, collector records, processor data, or manual corrections, and clarify how waste streams are classified. This is particularly important in waste-value ecosystems because

users may hesitate to rely on dashboard information when data are delayed, incomplete, reclassified, or not aligned with internal reporting categories. More transparent data-status information can therefore help users assess whether dashboard figures are suitable for reporting, discussion, or follow-up.

Second, platform providers can support contextual interpretation by helping users understand what dashboard signals may indicate in their specific waste context. This can be supported through clearer indicator explanations, sector-specific benchmarks, deviation alerts, explanatory labels, and drill-down functionality. For example, an increase in residual waste may reflect poor source separation, but it may also reflect a temporary project, production change, contamination of a separated stream, or a change in waste classification. Similarly, an increase in waste-related costs per kilogram may result from a change in treatment route, collection frequency, container filling rate, contamination surcharge, or contract condition. Dashboards that help users distinguish between these possible explanations can make waste-related information more meaningful and reduce the risk that figures remain visible but uninterpreted.

Third, platform providers can connect dashboard signals to possible follow-up routes. This does not mean that the platform should prescribe a single action, because the appropriate response depends on the organisation's operational and sectoral context. However, the platform can support users by suggesting relevant diagnostic questions or potential intervention categories. For example, a low separation percentage could trigger prompts to examine bin availability, contamination of separated streams, employee disposal instructions, location-level differences, or the feasibility of additional source-separation routes. A high cost per kilogram could prompt users to examine collection frequency, container efficiency, high-cost waste streams, alternative processing routes, or possibilities for compaction or cleaner separation. Such functionality would help users move from observing a deviation to identifying the type of organisational inquiry or follow-up that may be relevant.

Fourth, platform providers can help mitigate the monitoring-action gap by supporting role-specific dashboards and follow-up functionality. Different organisational actors need different forms of waste-related information. Sustainability or ESG users may need aggregated indicators for reporting and target monitoring, while facility managers may need location-level deviations, collection issues, container information, or contamination signals. Site managers may need practical information on their own location, while procurement or supplier-management actors may need information on packaging-related waste streams or recurring residual materials. Role-specific dashboards can therefore help direct information to users who are closer to relevant decisions or operational practices. In addition, functionality such as comments, action logs, task assignment, status tracking, or escalation fields can help connect dashboard observations to organisational follow-up responsibilities.

Fifth, platform providers can support feasible ecosystem-level follow-up by making external processing and revalorisation options more visible. In a waste-value ecosystem, circular-performance improvement often depends on collectors, processors, service providers, suppliers, or customers. The platform provider can support this by indicating available treatment routes, processor requirements, quality conditions for revalorisation, or reasons why a waste stream cannot currently be processed differently. For example, a dashboard may show a growing wood, plastic, organic, or packaging-related waste stream, but circular follow-up depends on whether that stream can be kept sufficiently clean, separately collected, accepted by a processor, and revalorised through an available route. By making these constraints and options more visible, the platform provider can help connect internal dashboard insights to external follow-up possibilities.

For client organisations, the findings suggest that dashboard use should be connected to routines and responsibilities. Assigning access to a dashboard or appointing a dashboard owner is not sufficient if no actor is responsible for interpreting the information or initiating follow-up. Organisations should therefore distinguish between dashboard ownership and action ownership. This means clarifying who monitors dashboard information, who interprets deviations, who has the mandate to decide on follow-up, who escalates issues to operational departments or suppliers, and who is responsible for implementation.

A second implication for client organisations is that dashboard information should be embedded in operational improvement routines, not only in reporting routines. ESG reporting, CSRD preparation, KPI reporting, and audit documentation can increase visibility and accountability, but they do not

automatically lead to circular-performance improvement. Organisations should therefore create recurring moments where dashboard insights are discussed in relation to operational practices. These moments may include management reviews, site-level meetings, facility or logistics meetings, supplier discussions, waste-reduction projects, or continuous-improvement routines. This helps mitigate the reporting-action gap by connecting waste-related information to decision-making, responsibility allocation, and evaluation.

A third implication is that organisations should develop internal interpretive capacity around waste-related information. The findings show that dashboard figures rarely speak for themselves. Users need to understand the organisation's waste streams, operational processes, sector-specific constraints, and available follow-up options in order to interpret whether a dashboard deviation reflects a problem, a contextual circumstance, or an improvement opportunity. Organisations can support this by involving operational staff, facility managers, sustainability specialists, procurement actors, and external waste partners in the interpretation of dashboard information. In this way, dashboard data can be connected to the process knowledge needed for meaningful follow-up.

For policymakers and institutional actors, the findings suggest that digital circularity should not be approached only as a transparency or reporting challenge. Existing reporting obligations can increase the demand for waste-related data, but the findings of this thesis show that visibility alone does not ensure circular-performance improvement. Additional policy efforts should therefore focus on the conditions that make waste-related platform information comparable, interpretable, exchangeable, and usable for circular follow-up across the waste-value ecosystem.

First, policymakers can support data confidence and contextual interpretation by developing or stimulating more specific data standards for digital waste platforms. Such standards could define common waste-stream categories, treatment-route definitions, data-status labels, and metadata requirements, including information on data source, update status, classification logic, and processing route. This would help reduce ambiguity when waste-producing organisations, platform providers, collectors, and processors use different classifications or reporting conventions for the same material stream.

Second, policymakers can support interoperability across the waste-value ecosystem. Circular follow-up often depends on information held by different actors, including waste-producing organisations, collectors, processors, and platform providers. Policy could therefore stimulate or require sectoral data-exchange protocols, API standards, or shared reporting formats that allow waste-related data to flow more consistently between these actors. This would make it easier to connect dashboard information on waste volumes, separation, costs, and environmental indicators to information about collection, treatment, processing, and revalorisation options.

Third, policymakers can complement reporting obligations with guidance and incentives for operational use of waste-related data. This may include sectoral benchmarks, best-practice guidance for using waste dashboards in improvement routines, support for pilots that use platform data to identify revalorisation opportunities, or requirements for large organisations to explain how material waste streams are monitored and followed up internally. Such measures would not prescribe specific organisational actions, but would support the routines, responsibilities, and learning processes through which waste-related information can become connected to circular-performance improvement.

Taken together, these implications suggest that the challenge is not only to make waste-related information visible, but also to strengthen the conditions under which such information becomes comparable, interpretable, embedded in organisational routines, and feasible to act upon within the wider waste-value ecosystem. This is the practical relevance of the actionable engagement mechanism: it identifies where different actors can intervene to move digital circular-economy platforms beyond transparency towards circular-performance improvement.

10.7. Limitations and directions for future research

This study has three main limitations.

First, the actionable engagement mechanism was empirically specified within one integrated platform ecosystem. Although the mechanism builds on several literature streams and the embedded case-study design includes internal variation across client organisations, the empirical setting remains specific. Milgro's platform has an integrated character because it combines operational, financial, environmental, and reporting-related information across the waste-value chain within a single digital environment.. The empirically specified form of the mechanism should therefore not be assumed to apply in the same way to more function-specific digital tools, such as platforms that primarily support logistics optimisation, route planning, waste administration, CSRD reporting, or other compliance-related functions. Future research should therefore examine whether the mechanism requires different specifications in other circularity contexts, such as product-passport platforms, material-exchange marketplaces, logistics platforms, or compliance-focused reporting tools, where the relation between information visibility, organisational control, and circular follow-up may differ.

Second, the qualitative phase used purposive sampling based on the engagement-performance profiles identified in the quantitative analysis. This sampling strategy was appropriate for gaining explanatory insight into the mechanisms underlying observed differences in platform engagement and circular performance. It also supported the development of the actionable engagement mechanism. However, the interview findings do not show whether the explanations identified in each profile are representative of all organisations within that profile. Nor do they show how common these mechanisms are across the broader population of platform users. Future research using a broader and more systematically sampled set of organisations could assess the prevalence and relative importance of the identified mechanisms.

Third, the study is based on the observation period from 2024Q1 to 2025Q4. This period provides a recent empirical window into platform engagement and circular-performance indicators, but it does not account for how long client organisations had already been using the dashboards before the observation period. It also does not fully capture the timing and influence of relevant regulatory developments during or before this period. As a result, the study cannot determine whether engagement and actionability differ across stages of platform use, or whether they change in response to evolving institutional and regulatory conditions. Longitudinal research could therefore contribute to a better understanding of whether, and under which conditions, the actionable engagement mechanism changes over time.

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A | Detailed Quantitative Data Preparation

This appendix provides additional technical detail on the quantitative data preparation procedure described in Chapter 6. Whereas Chapter 6 explains the methodological logic and analytical implications of the data preparation process, this appendix documents the dataset-specific steps, intermediate dataset sizes, completeness checks, and feature-table construction decisions used to create the final analytical dataset.

The quantitative analysis is based on operational records from Milgro's internal systems. These records were generated as part of regular platform and service processes and therefore required additional preparation before they could be used for academic analysis. The preparation steps documented in this appendix were used to improve consistency across source systems and to construct a harmonised company-quarter dataset for quantitative analysis.

A.1. Cleaned source-level datasets

Table A.1 reports the cleaned source-level dataset sizes after dataset-specific cleaning and the final cross-dataset consistency check. These files formed the basis for aggregation into company-quarter feature tables.

Table A.1: Cleaned source-level dataset sizes before aggregation.

Dataset	Rows	Analytical role
Customer characteristics	1,716	Context variables and matching reference
Standard order channel data	12,972	Routine transactional engagement
Total orders data	29,022	Denominator for relative indicators
Scores data	1,205	Circular performance indicators
Dashboard data	1,256	Informational dashboard engagement
Support data	28,086	Support-related engagement
Incident & damage/malfunction data	3,003	Non-routine operational engagement

A.2. Initial standardisation procedures

All source files were first standardised at the column-name level using a shared cleaning routine. Column names were converted to lowercase, byte-order marks and formatting artefacts were removed, punctuation was normalised, and spaces or irregular characters were replaced by underscores. This created a consistent naming convention across datasets that had originally been structured differently.

Because the matching procedure relied heavily on company and branch names, textual normalisation formed a central part of the preprocessing pipeline. Raw names contained variation in capitalisation, punctuation, legal suffixes, spacing, and encoding. To reduce these inconsistencies, all relevant text variables were normalised using shared helper functions. These functions stripped whitespace, converted text to lowercase, removed or standardised punctuation, and harmonised common company-name variants.

Two related but distinct standardisation procedures were used. A general text-normalisation function was applied to descriptive text fields, while a key-specific standardisation function was used to construct company-level and branch-level match keys. The latter removed non-informative substrings, harmonised common abbreviations, and reduced spelling variation, thereby producing keys that were better suited for deterministic and semi-deterministic matching.

Several datasets stored the time variable in a compact text format, such as 2024Q1. These strings were parsed into separate `jaar` and `kwartaal` variables. Numeric variables stored as text were converted to numeric format. This was particularly relevant for the scores dataset, where values such as separation

percentage, costs per kilogram, and CO₂-equivalent emissions per kilogram were initially stored as strings and sometimes used decimal commas instead of decimal points.

A.3. Dataset-specific preparation

A.3.1. Customer characteristics

The customer characteristics dataset was cleaned to retain the variables required for contextual analysis and entity matching. The main variables retained were company name, branch name, sector classification, country code, and location characteristics. Duplicate observations were removed after standardisation.

After the final cross-dataset consistency check, the cleaned customer characteristics dataset contained 1,716 rows and represented 166 unique companies. This file served as the main contextual reference for sector, country, and location-related explanatory variables. It also formed an important lookup source in the matching process.

A.3.2. Standard order channel data

The standard-order channel dataset was prepared to capture how routine orders were distributed across available channels. After cleaning and temporal parsing, the file was converted into a company-quarter-channel structure containing company name, company key, branch name, branch key, year, quarter, channel, and number of orders.

This cleaned source dataset contained 12,972 rows. It was later aggregated into a feature table with one row per company-quarter and one column per routine-order channel. The resulting feature table contained 1,177 company-quarter observations covering 182 unique companies.

For each company-quarter, a total number of standard orders was calculated, as well as the number of routine-order channels used in that quarter. These variables were subsequently used to derive routine-channel shares, such as the share of standard orders placed through the portal, app, OBO, and SLIMS.

A.3.3. Total orders data

The total-orders dataset was used as the main denominator file in the analysis. After dataset-specific cleaning, temporal parsing, filtering to the common analytical window, and the final cross-dataset consistency check, the data were aggregated to the company-quarter level.

The final cleaned total-orders source dataset contained 29,022 rows and covered 193 unique companies. The corresponding feature table contained 1,247 company-quarter observations and covered 193 unique companies. Because this file was later used to normalise multiple engagement measures, completeness checks were performed to examine quarter coverage across companies.

A.3.4. Dashboard data

The dashboard dataset was originally stored in wide format, with quarter-specific values spread across columns. These fields were standardised and reshaped into a long company-quarter structure. Missing dashboard-view values were set to zero, and a binary indicator was constructed to capture whether dashboard use occurred in a given quarter.

After the final cross-dataset consistency check, the resulting long-format dashboard table contained 1,256 rows and 157 unique companies. This same table functioned directly as the dashboard feature table.

A.3.5. Scores data

The scores dataset contained company-quarter values for separation percentage, costs per kilogram, and CO₂-equivalent per kilogram of waste. After cleaning, temporal parsing, and numeric conversion, only the relevant variables were retained.

The cleaned scores feature table contained 1,205 company-quarter observations and covered 183 unique companies.

A.3.6. Support data

The support dataset required the most extensive entity-resolution procedure because support records did not align directly with the cleaned customer master data. Support records were first cleaned by standardising subsidiary names, extracting year and quarter from ticket timestamps, and harmonising channel labels. Records with invalid subsidiary names, unknown channels, or observations outside the analytical period were removed.

As an additional validation step, only support records were retained for which the support `company_id` matched a `record_id` in the `ontdoener` reference file for observations with `type = ontdoener`. This restriction ensured that the support dataset was limited to organisations belonging to the relevant analytical population. After this filtering step, 28,613 support observations remained.

The detailed hierarchical matching procedure for support records is documented in Appendix B. After all matching and dataset-specific cleaning steps, the support dataset contained 28,087 source-level observations and covered 179 unique companies. Following the final cross-dataset consistency check, the derived support feature table contained 797 company-quarter observations and covered 178 unique companies.

A.3.7. Incident and damage/malfunction data

The incident and damage/malfunction dataset was cleaned in a similar way, but required an additional categorisation step. Raw event categories were standardised and collapsed into two analytically relevant groups: *incidental orders* and *damage/malfunction events*. Records with invalid subsidiary names, observations outside the common time window, or unknown channels were removed.

The cleaned source file contained 3,003 rows and covered 150 unique matched companies. The detailed preparation and matching procedure for this dataset is documented in Appendix C. The cleaned incident and damage/malfunction file was aggregated by company, quarter, channel, and cleaned category. The resulting feature table contained 605 company-quarter observations and covered 150 unique companies.

A.4. Cross-dataset consistency check

After all source datasets had been cleaned individually, a final cross-dataset consistency check was performed before constructing the feature tables. In this step, company keys that appeared in only one cleaned source dataset were identified and reviewed. Such entities were removed where their inclusion would not contribute meaningfully to the integrated multi-source analysis.

This affected 55 observations in the customer characteristics dataset, 14 observations in the total-orders dataset, 8 observations in the dashboard dataset, and 1 observation in the support dataset. No such removals were required for the standard-order, scores, or incident and damage/malfunction datasets.

This check took place after dataset-specific cleaning and matching, but before the construction of the company-quarter feature tables. The feature tables therefore reflect the final set of entities retained for the integrated analysis.

A.5. Company-quarter completeness

Before merging, the temporal coverage of the main company-quarter datasets was assessed by comparing the observed year-quarter combinations for each company with the full analytical window from 2024Q1 to 2025Q4.

For datasets that capture recurring organisational activity, such as total orders, standard orders, scores, and dashboard use, this check was used to assess whether company-quarter coverage was structurally complete. For support and incident and damage/malfunction data, the same check was interpreted differently because these datasets capture event-driven interactions rather than recurring baseline activity. The absence of a company in a given quarter may therefore indicate that no support contact or incident occurred, rather than incomplete source coverage.

Table A.2: Company-quarter completeness across recurring datasets.

Dataset	Companies with complete coverage	Interpretation
Total orders	119 companies	Recurring operational activity
Standard orders	112 companies	Recurring routine order activity
Scores	117 companies	Recurring circular performance data
Dashboard	All companies in dashboard source	Dashboard source coverage

The completeness check was used to interpret variable-specific sample sizes and to assess whether missing company-quarter observations reflected data availability, non-use, or event-driven sparsity.

A.6. Company-quarter feature tables

After the final dataset-specific cleaning steps and the cross-dataset consistency check, separate company-quarter feature tables were constructed for the main behavioural and contextual domains.

Table A.3: Company-quarter feature table sizes after aggregation.

Feature table	Rows	Unique companies
Standard-order features	1,177	182
Dashboard features	1,256	157
Scores features	1,205	183
Total-orders features	1,247	193
Support features	797	178
Incident and damage/malfunction features	605	150
Context features	166	166

The feature-table quality checks showed no missing company keys in the aggregated feature tables.

A.7. Feature construction

A.7.1. Routine channel variables

The standard-order feature table was pivoted by routine-order channel to create quarter-level counts per channel. From this table, two additional variables were derived: the total number of standard orders per company-quarter and the number of routine-order channels used. Relative routine-channel variables were then created for portal, app, OBO, and SLIMS.

A.7.2. Dashboard variables

From the dashboard feature table, two central variables were retained: `dashboard_views`, capturing the total number of dashboard views in a company-quarter, and `dashboard_actief`, a binary indicator equal to 1 if dashboard use occurred in that quarter.

A.7.3. Support variables

The support feature table was pivoted by support channel, producing quarter-level counts for e-mail, telephone, portal, chat, and where applicable other support channels. From this, the total number of support interactions and the number of support channels used in a quarter were calculated. Relative support-channel shares were then derived.

A.7.4. Incident and damage/malfunction variables

The incident and damage/malfunction feature table was pivoted by combined category-channel combinations. This yielded quarter-level counts for incidental orders and damage/malfunction events across different channels. From these values, aggregate variables were constructed for incidental orders, damage/malfunction events, and total incidents.

A.7.5. Context variables

A contextual feature table was created by aggregating the customer characteristics dataset to one row per company. For each company, the first non-missing sector, country code, and location descriptor were retained. This table introduced structural explanatory variables into the integrated analytical file.

A.8. Merge procedure

To merge the feature tables consistently, a master company-quarter grid was first constructed by concatenating the company-quarter keys from the main feature tables and removing duplicates. This master grid represents the union of all observed company-quarter combinations across the data sources used for the engagement analysis.

The resulting master grid contained 1,415 company-quarter observations and covered 196 unique companies. The feature tables were then merged sequentially onto this master grid using the keys `bedrijf_key`, `jaar`, and `kwartaal`. Company names were reattached afterwards through a separate lookup step, and context variables were merged separately at the company level.

This merge strategy produced an intermediate quarter-level analytical file with 1,415 rows and 55 columns. The identical number of rows before and after merging indicates that the feature tables were merged without introducing duplicate company-quarter observations.

Figure A.1 visualises the integration of the company-quarter feature tables into the final analytical dataset.

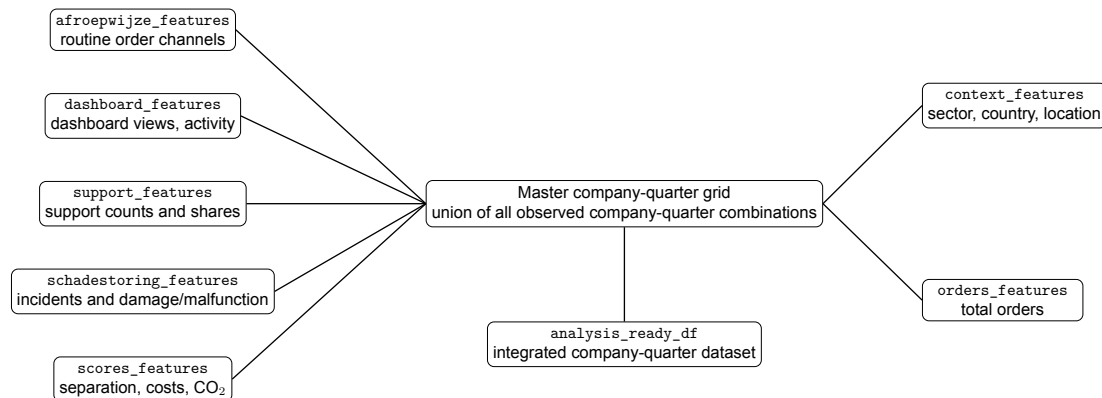


Figure A.1: Integration of company-quarter feature tables into the final analytical dataset through the master company-quarter grid.

A.9. Normalisation and additional transformations

Several count-based engagement variables were normalised by total order volume and expressed per 100 orders. This was done to improve comparability between organisations of different operational sizes. The main relative variables constructed were:

- `dashboard_views_per_100_orders`
- `support_per_100_orders`
- `incidentele_orders_per_100_orders`
- `schade_storing_per_100_orders`

Channel-based variables were expressed as proportions of their corresponding totals, such as routine-order shares and support-channel shares. This allowed comparison of both engagement intensity and engagement composition.

For exploratory purposes, log-transformed versions of several heavily skewed variables were also constructed, including total orders, standard orders, support totals, dashboard views, and incident and damage/malfunction totals. These transformations were used only for exploratory checks. The main SQ1 analyses rely primarily on the relative engagement measures.

A.10. Final analytical dataset

After zero-filling of structural non-use variables and construction of relative engagement measures, the final integrated company-quarter dataset, referred to in the notebooks as `analysis_ready_df`, contained 1,415 rows and 67 columns. It covered 196 unique companies.

The dataset includes routine order channel counts and shares, dashboard usage variables, support interaction counts and shares, incident and damage/malfunction variables, total order volume, sustainability indicators, contextual company characteristics, and derived relative engagement measures.

Because not all variables were observed for all companies and quarters, the effective number of observations differs across indicators and analyses. The final company-quarter dataset forms the empirical basis for SQ1 and is subsequently aggregated to the organisational level where required for SQ2.

A.11. Reproducibility note

The preprocessing steps were implemented in Python notebooks. These notebooks contain the executable data-cleaning, matching, aggregation, and feature-engineering procedures underlying the dataset described in Chapter 6 and this appendix.

Due to confidentiality restrictions, the raw operational data cannot be shared publicly. However, the methodological steps, intermediate dataset sizes, matching procedures, and feature-construction decisions are documented in the thesis to provide a transparent audit trail.

B | Support Matching Procedure

This appendix documents the hierarchical matching procedure used to assign support records to harmonised company identifiers. The support dataset required a separate matching procedure because support records did not align directly with the cleaned customer characteristics dataset. The procedure was designed to maximise reliable assignment while avoiding unsupported matches.

B.1. Initial filtering and validation

Support records were first cleaned by standardising subsidiary names, extracting year and quarter from ticket timestamps, and harmonising channel labels. Records with invalid subsidiary names, unknown channels, or observations outside the analytical period were removed.

As an additional validation step, only support records were retained when the support `company_id` matched a `record_id` in the `ontdoener` reference file for observations with `type = ontdoener`. This ensured that the support dataset was limited to organisations belonging to the relevant analytical population. After this filtering step, 28,613 support observations remained.

B.2. Matching hierarchy

The matching procedure followed a hierarchical logic. Records were first matched using the most specific and reliable available information. Remaining unmatched records were then passed through progressively broader matching steps.

1. Branch-level matching using `debname` in the customer characteristics reference file.
2. Company-level matching using `rootname` in the customer characteristics reference file.
3. Recovery through exact raw-name matches in the total-orders dataset.
4. Recovery through standard-order data.
5. Partial branch-level matching.
6. Loose partial matching.
7. Manual assignment for residual cases that were substantively important and could be assigned reliably.

The purpose of the matching procedure was not to maximise the number of retained records at all costs, but to construct a reliable company-level representation of support interactions. Records were only retained when they could be assigned to a company with sufficient confidence.

B.3. Match distribution

After all matching and dataset-specific cleaning steps, the support dataset contained 28,087 source-level observations and covered 179 unique companies. Following the final cross-dataset consistency check, the derived support feature table contained 797 company-quarter observations and covered 178 unique companies.

Table B.1: Final match distribution for the support dataset.

Match type	Number of records
debname_match	21,901
rootname_match	3,715
totaalorders_raw_exact_match	1,172
manual_match	935
afroep_loose_partial_match	319
partial_filial_match	45

B.4. Support matching flowchart

Figure B.1 visualises the hierarchical matching procedure used to assign support records to harmonised company identifiers before aggregation to the company-quarter feature table.

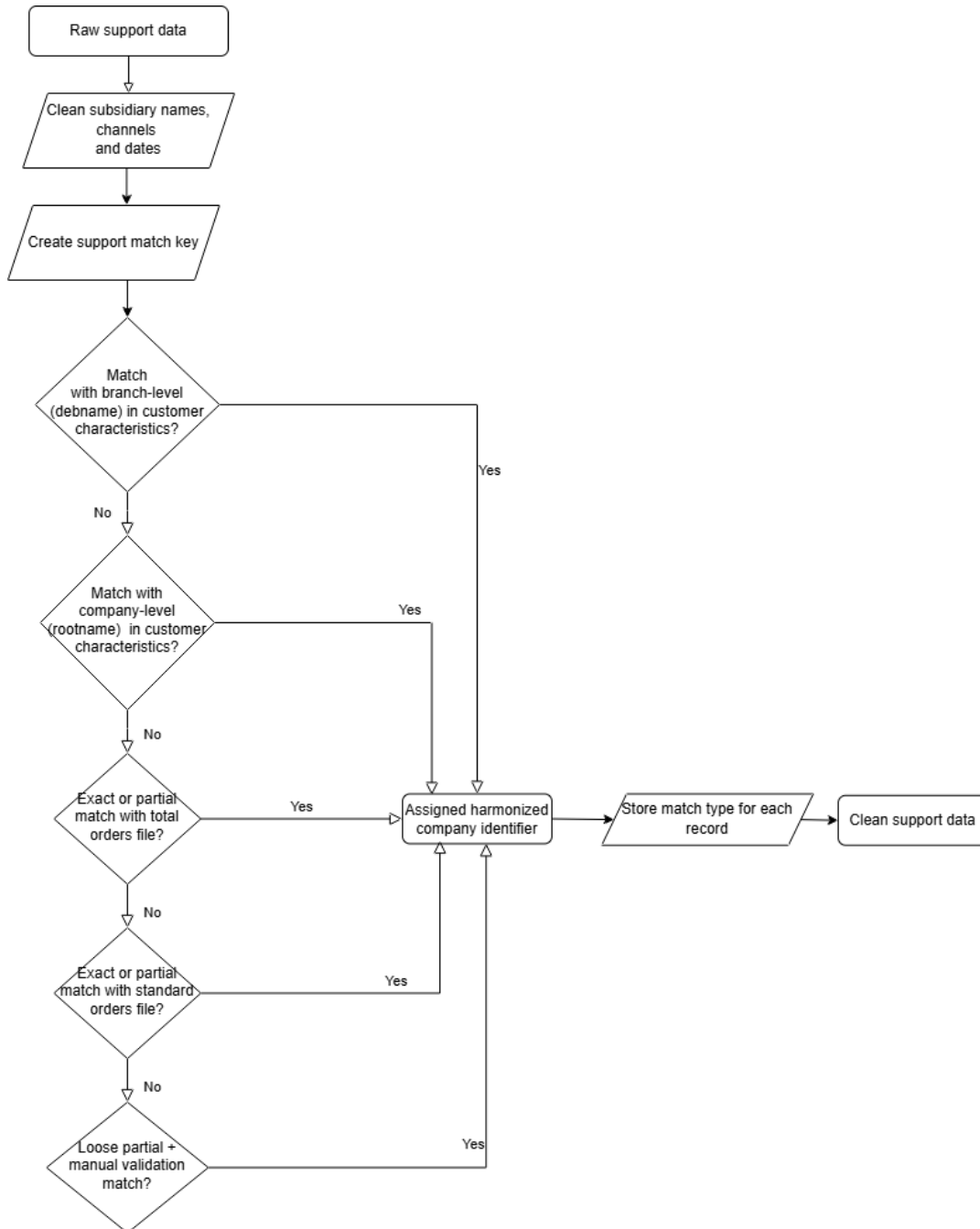


Figure B.1: Hierarchical support-matching procedure used to assign support records to harmonised company identifiers before aggregation to the company-quarter feature table.

B.5. Interpretation

The hierarchical matching strategy reduced dependence on a single identifier and combined deterministic branch-level and company-level matching, recovery through auxiliary datasets, partial matching logic, and manual validation. This improved the consistency of company-level support indicators while limiting the risk of assigning support interactions to incorrect organisations.

C | Incident and Damage/Malfunction Data Preparation

This appendix documents the preparation of the incident and damage/malfunction dataset. The raw dataset required both categorisation and entity matching before it could be aggregated into company-quarter indicators for non-routine operational engagement.

C.1. Event categorisation

The incident and damage/malfunction dataset captured non-routine interactions, including incidental orders and damage or malfunction events. Raw event categories were standardised and collapsed into two analytically relevant groups: incidental orders and damage/malfunction events. Records with invalid subsidiary names, unknown channels, or observations outside the analytical window were removed. This categorisation step was necessary because the raw event labels were not directly aligned with the conceptual distinction used in the thesis. The resulting categories allowed non-routine operational engagement to be analysed separately from routine order behaviour and support-related engagement.

C.2. Matching procedure

The cleaned source file contained 3,003 rows and covered 150 unique matched companies. Matching proceeded hierarchically. First, incident and damage/malfunction records were linked through support-derived matching keys where possible. Second, remaining observations were matched through branch-level and company-level names using the cleaned customer reference data. Third, additional recovery was attempted through the total-orders file and the standard-order file, using raw exact, standardised exact, and partial matching logic. Finally, a small number of residual records were resolved manually when assignment was reliable. The matching procedure was designed to ensure that incident and damage/malfunction records could be aggregated to the same harmonised company identifiers used in the other feature tables.

C.3. Match distribution

The final match distribution for the incident and damage/malfunction file is reported in Table C.1.

Table C.1: Final match distribution for the incident and damage/malfunction dataset.

Match type	Number of records
support_match	2,930
totalorders_raw_exact_match	49
debname_match	18
manual_match	5
rootname_match	1

C.4. Aggregation into feature table

After categorisation and matching, the cleaned incident and damage/malfunction file was aggregated by company, quarter, channel, and cleaned event category. This produced company-quarter indicators for incidental orders, damage/malfunction events, total non-routine incidents, and, where possible, channel-specific variables. The resulting feature table contained 605 company-quarter observations and covered 150 unique companies. These variables were used to analyse non-routine operational engagement as one dimension of organisational platform engagement.

C.5. Interpretation

Incident and damage/malfunction records capture event-driven interactions rather than recurring baseline activity. Therefore, the absence of a record in a company-quarter should not automatically be interpreted as missing data. In many cases, it indicates that no non-routine incident or damage/malfunction was recorded for that organisation in that quarter. This interpretation differs from recurring datasets such as total orders or performance scores, where missingness is more likely to reflect limited data availability.

D | Supplementary quantitative results for SQ1: platform use across organisations

This appendix reports supplementary descriptive tables, diagnostic checks, post-hoc results, and figures for SQ1. These materials support the quantitative results reported in Chapter 7.

The appendix is organised as follows. Section D.1 reports the descriptive statistics for the main engagement indicators. Section D.2 provides additional channel-use descriptives. Section D.3 reports sector-level descriptives and supplementary sector visualisations. Section D.4 reports customer-size descriptives and post-hoc test results. Section D.5 documents supplementary location-group and country-code checks.

D.1. General engagement descriptives

Table D.1 reports descriptive statistics for the main relative engagement indicators at the organisational level. The indicators show right-skewed distributions, particularly for dashboard views per 100 orders and support tickets per 100 orders. This supports the use of medians, visualisations, and non-parametric tests in Chapter 7.3.

Table D.1: Descriptive statistics of general relative engagement indicators at the organisational level

Indicator	Count	Mean	Std. dev.	Min	25%	Median	75%	Max
Dashboard views per 100 orders	193	11.361	27.467	0.000	1.115	5.290	11.472	328.618
Dashboard activity	196	0.624	0.407	0.000	0.125	0.813	1.000	1.000
Support tickets per 100 orders	193	8.648	11.767	0.000	2.408	5.372	9.911	100.000
Incidental orders per 100 orders	193	1.108	5.360	0.000	0.000	0.313	0.693	50.000
Damage/malfunction reports per 100 orders	193	0.198	0.461	0.000	0.000	0.031	0.253	5.228

D.2. Channel-use descriptives

This section reports additional descriptive statistics and figures for routine, support-related, and non-routine channel use. These materials provide supplementary detail for the multidimensional interpretation of platform use in Chapter 7.3.3.

D.2.1. Routine channel use

Table D.2 reports the distribution of standard orders across routine channels. The portal has the highest mean and median share, followed by SLIMS. App and OBO channels account for smaller shares on average.

Table D.2: Descriptive statistics of routine channel shares

Indicator	Count	Mean	Std. dev.	Min	25%	Median	75%	Max
Portal share of standard orders	196	0.493	0.328	0.000	0.171	0.522	0.791	1.000
App share of standard orders	196	0.083	0.189	0.000	0.000	0.000	0.050	0.958
OBO share of standard orders	196	0.032	0.063	0.000	0.000	0.010	0.033	0.443
SLIMS share of standard orders	196	0.155	0.152	0.000	0.046	0.114	0.209	1.000

Figure D.1 visualises the mean share of standard orders by routine channel.

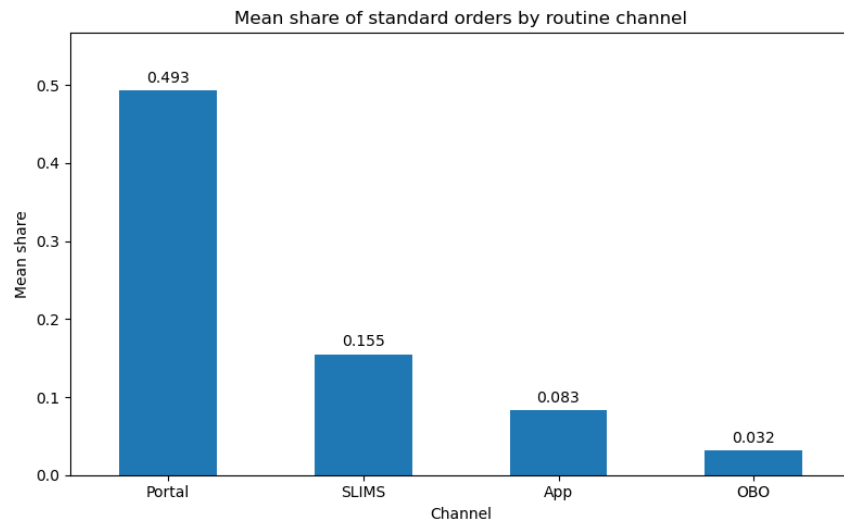


Figure D.1: Mean share of standard orders by routine channel

D.2.2. Support channel use

Table D.3 reports the distribution of support interactions across channels. E-mail has the highest average and median share, while telephone also plays a relevant role. Portal and chat are used less intensively. This supports the interpretation that support-related engagement remains more dependent on direct communication channels than routine transactional engagement.

Table D.3: Descriptive statistics of support channel shares

Indicator	Count	Mean	Std. dev.	Min	25%	Median	75%	Max
E-mail share of support tickets	196	0.401	0.226	0.000	0.249	0.439	0.537	1.000
Telephone share of support tickets	196	0.081	0.082	0.000	0.011	0.066	0.122	0.458
Portal share of support tickets	196	0.053	0.066	0.000	0.000	0.035	0.081	0.500
Chat share of support tickets	196	0.010	0.032	0.000	0.000	0.000	0.010	0.404

Figure D.2 shows how many organisations use each support channel. It complements the support-channel shares by showing that e-mail and telephone are not only important in terms of average share, but are also used by many organisations.

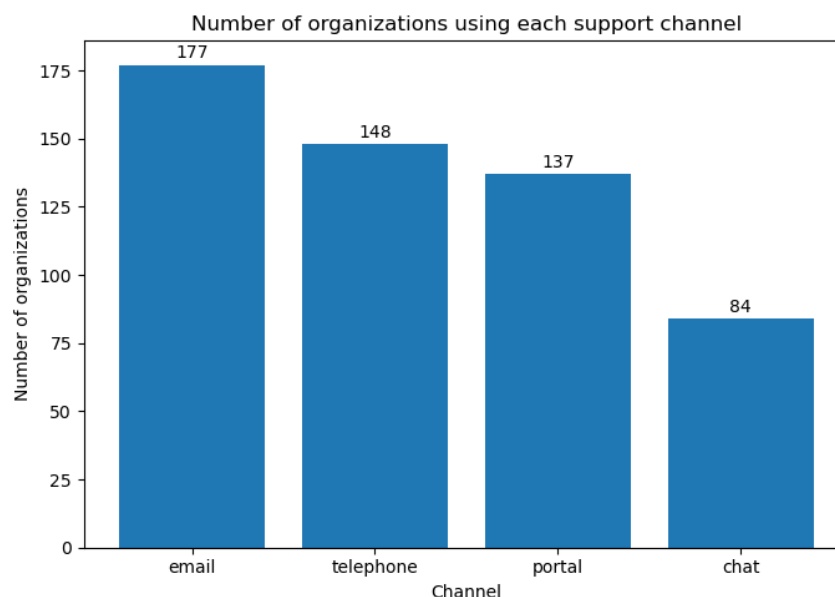


Figure D.2: Number of organisations using each support channel

D.2.3. Non-routine channel use

Table D.4 reports channel shares for incidental orders and damage/malfunction reports. Many medians are equal to zero, which means that several channels are not used at all by many organisations. E-mail is the dominant channel for both incidental orders and damage/malfunction reports, while telephone and portal are used more selectively. This supports the interpretation that non-routine engagement is more fragmented and organisation-specific than routine engagement.

Table D.4: Descriptive statistics of non-routine channel shares

Indicator	Count	Mean	Std. dev.	Min	25%	Median	75%	Max
Chat share of incidental orders	143	0.012	0.056	0.000	0.000	0.000	0.000	0.500
E-mail share of incidental orders	143	0.744	0.287	0.000	0.539	0.800	1.000	1.000
Form share of incidental orders	143	0.004	0.042	0.000	0.000	0.000	0.000	0.500
Portal share of incidental orders	143	0.119	0.205	0.000	0.000	0.000	0.204	1.000
Telephone share of incidental orders	143	0.120	0.234	0.000	0.000	0.000	0.125	1.000
Chat share of damage/malfunction reports	104	0.007	0.037	0.000	0.000	0.000	0.000	0.250
E-mail share of damage/malfunction reports	104	0.678	0.374	0.000	0.500	0.805	1.000	1.000
Form share of damage/malfunction reports	104	0.005	0.049	0.000	0.000	0.000	0.000	0.500
Portal share of damage/malfunction reports	104	0.101	0.226	0.000	0.000	0.000	0.057	1.000
Telephone share of damage/malfunction reports	104	0.210	0.330	0.000	0.000	0.000	0.322	1.000

Figure D.3 visualises how many organisations use each channel for non-routine interactions. This supports the interpretation that non-routine engagement is more fragmented and selective than routine engagement.

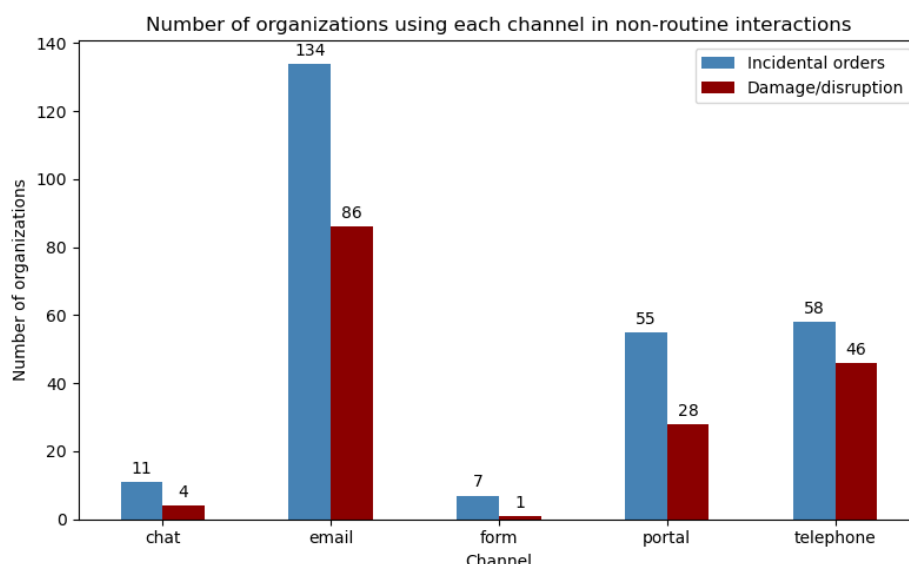


Figure D.3: Number of organisations using each channel in non-routine interactions

Together, the channel-use descriptives show that different forms of engagement are routed through different channels. Routine interactions are more structured, support interactions rely more strongly on direct communication, and non-routine interactions are more fragmented.

D.3. Additional sector-level descriptives

Tables D.5–D.8 report sector-level descriptive statistics underlying the sector comparison in Chapter 7.4. Because the number of observations differs across variables, variable-specific counts are shown underneath each sector mean. Sector groups with very small numbers of observations are included for transparency, but should not be interpreted as robust sector-level patterns.

Table D.5: Sector-level mean values and counts for general engagement indicators

Sector	Dashboard views/100	Dashboard activity	Support/100	Incident/100	Damage/malfunction/100
Construction & Industry	20.1515	0.7284	8.5171	2.0850	0.1110
<i>N</i>	29	29	29	29	29
Food	14.2134	0.7254	10.3716	0.5121	0.3024
<i>N</i>	66	66	66	66	66
Government	6.1411	0.2500	7.4006	0.7058	0.0276
<i>N</i>	2	3	2	2	2
Healthcare	43.1383	0.6250	59.5193	0.7177	0.2902
<i>N</i>	1	1	1	1	1
Infra & Energy	3.8208	0.9688	5.7793	0.5265	0.0295
<i>N</i>	4	4	4	4	4
Logistics	8.4261	0.7552	10.7421	0.7852	0.4281
<i>N</i>	24	24	24	24	24
Mobility	8.1449	0.7169	7.5088	0.2129	0.0365
<i>N</i>	34	34	34	34	34
Resellers	NaN	0.0000	NaN	NaN	NaN
<i>N</i>	0	1	0	0	0
Retail	3.2828	0.5938	2.9319	0.1551	0.0650
<i>N</i>	3	4	3	3	3

Table D.6: Sector-level mean values and counts for routine channel shares

Sector	Portal share	App share	OBO share	SLIMS share
Construction & Industry <i>N</i>	0.4973 29	0.1931 29	0.0252 29	0.0902 29
Food <i>N</i>	0.4957 66	0.1062 66	0.0280 66	0.1468 66
Government <i>N</i>	0.1265 3	0.0027 3	0.0058 3	0.1150 3
Healthcare <i>N</i>	0.1673 1	0.1788 1	0.0087 1	0.1370 1
Infra & Energy <i>N</i>	0.7524 4	0.0532 4	0.0241 4	0.1704 4
Logistics <i>N</i>	0.4077 24	0.0892 24	0.0447 24	0.1719 24
Mobility <i>N</i>	0.6241 34	0.0120 34	0.0313 34	0.1928 34
Resellers <i>N</i>	0.0000 1	0.0000 1	0.0000 1	0.0000 1
Retail <i>N</i>	0.5345 4	0.0164 4	0.0086 4	0.0496 4

Table D.7: Sector-level mean values and counts for support channel shares

Sector	E-mail share	Telephone share	Portal share	Chat share
Construction & Industry <i>N</i>	0.3869 29	0.0853 29	0.0614 29	0.0080 29
Food <i>N</i>	0.4336 66	0.0907 66	0.0401 66	0.0119 66
Government <i>N</i>	0.4458 3	0.0660 3	0.0600 3	0.0110 3
Healthcare <i>N</i>	0.5125 1	0.0760 1	0.0235 1	0.0044 1
Infra & Energy <i>N</i>	0.5341 4	0.1209 4	0.0828 4	0.0120 4
Logistics <i>N</i>	0.5133 24	0.1043 24	0.0759 24	0.0079 24
Mobility <i>N</i>	0.4070 34	0.0849 34	0.0897 34	0.0135 34
Resellers <i>N</i>	0.5833 1	0.3333 1	0.0000 1	0.0833 1
Retail <i>N</i>	0.6201 4	0.0874 4	0.0293 4	0.0083 4

Table D.8: Sector-level mean values and counts for non-routine channel shares

Sector	Incident e-mail	Incident portal	Incident tel.	Damage e-mail	Damage portal	Damage tel.
Construction & Industry <i>N</i>	0.7711 22	0.1175 22	0.0950 22	0.7071 17	0.0735 17	0.2047 17
Food <i>N</i>	0.7911 52	0.0829 52	0.1101 52	0.6545 41	0.0991 41	0.2308 41
Government <i>N</i>	0.6442 2	0.1898 2	0.1581 2	0.7500 1	0.2500 1	0.0000 1
Healthcare <i>N</i>	0.4083 1	0.4167 1	0.1750 1	0.5625 1	0.0625 1	0.3750 1
Infra & Energy <i>N</i>	0.7697 4	0.1759 4	0.0513 4	0.5000 2	0.5000 2	0.0000 2
Logistics <i>N</i>	0.7903 20	0.1759 20	0.0282 20	0.6556 16	0.1531 16	0.1891 16
Mobility <i>N</i>	0.5682 24	0.2124 24	0.1999 24	0.8444 15	0.0722 15	0.0667 15
Resellers <i>N</i>	NaN 0	NaN 0	NaN 0	0.0000 1	0.0000 1	1.0000 1
Retail <i>N</i>	0.9333 3	0.0000 3	0.0667 3	0.4000 3	0.1000 3	0.5000 3

Taken together, these sector-level descriptives show that sector differences are not limited to one indicator. Sectors differ across dashboard use, support intensity, routine channel allocation, and non-routine interaction patterns. However, several sector groups contain very small numbers of organisations. The sector means should therefore be read as descriptive support for the main analysis, not as robust sector-level estimates.

The following figures provide additional visual support for the sector-level patterns. They are included here because they complement the sector descriptives and the Kruskal–Wallis results reported in Chapter 7.4.

Figure D.4 shows that support intensity varies across sectors. The figure should be read descriptively, because several sector groups contain few organisations.

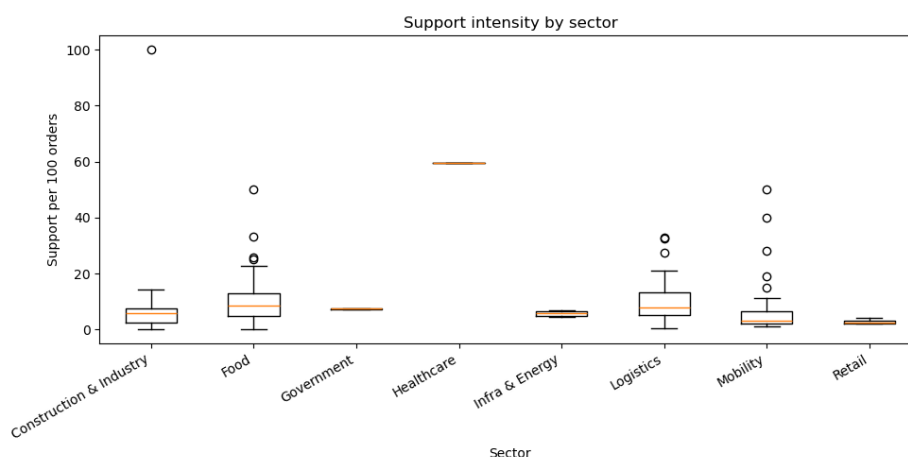
**Figure D.4:** Support intensity by sector

Figure D.5 summarises sector-level differences across selected engagement indicators. The values are z-standardised sector means. A positive value indicates that a sector scores above the overall sector mean for that indicator, while a negative value indicates a below-average score. The figure supports the multidimensional interpretation of engagement: sectors differ not only in dashboard use, but also in support intensity, non-routine interactions, and routine channel preferences.



Figure D.5: Heatmap of z-standardised engagement indicators by sector

The sector heatmap should be interpreted cautiously for sectors with very small numbers of organisations, especially Healthcare, Government, Retail, and Infra & Energy. For these sectors, the figure is useful as descriptive support, but not as evidence of robust sector-level effects.

Figure D.6 visualises the mean distribution of routine standard orders across channels by sector. It supports the sector discussion in Chapter 7 by showing that sectors differ not only in dashboard use or support intensity, but also in how routine interactions are routed. Portal use is dominant in several sectors, while SLIMS plays a more visible role in sectors such as Food, Logistics, Mobility, and Infra & Energy.

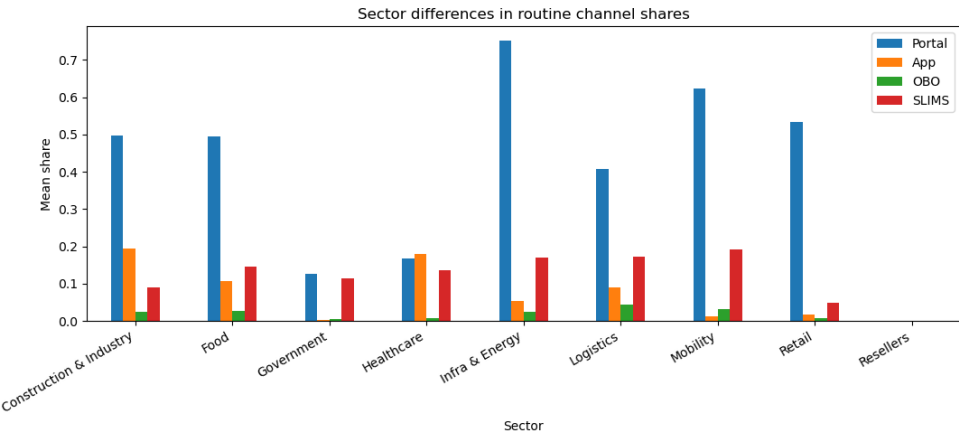


Figure D.6: Mean routine channel shares by sector

Figure D.7 provides an additional sector-level visualisation of portal use. Compared with Figure D.6, this figure focuses specifically on the spread of portal use within each sector. It shows that sectors differ not only in their average portal share, but also in the extent of within-sector variation.

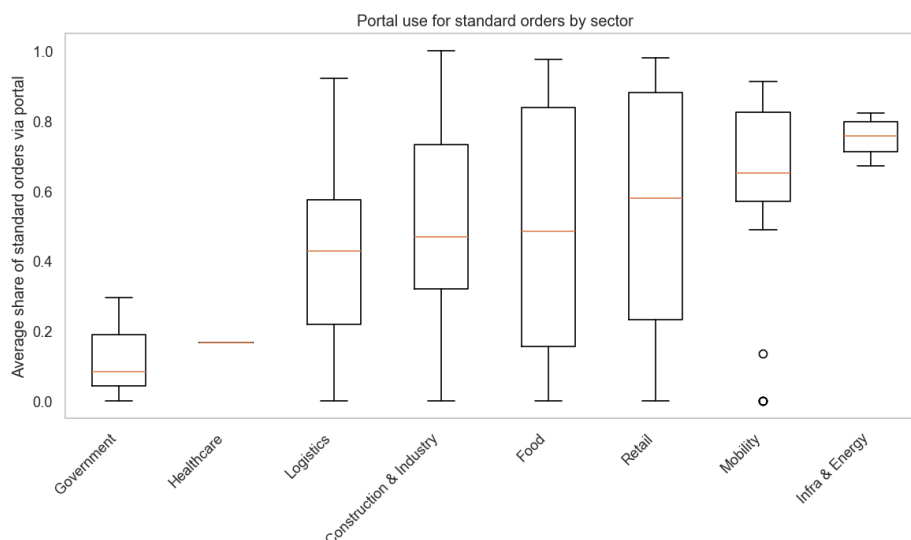


Figure D.7: Portal share of standard orders by sector

D.4. Additional customer-size descriptives and post-hoc tests

This section provides supplementary information for the customer-size comparison in Chapter 7.4.2. Customer size was operationalised using tertiles of average total order volume. The tables below show how routine, support-related, and non-routine channel patterns differ across small, medium-sized, and large organisations.

Table D.9: Customer-size mean values and counts for general engagement indicators

Customer size	Dashboard views/100	Dashboard activity	Support/100	Incident/100	Damage/malfunction/100
Small	18.6800	0.2923	12.2576	2.0484	0.1777
<i>N</i>	62	65	62	62	62
Medium	8.8084	0.6808	7.0730	0.5465	0.2367
<i>N</i>	65	65	65	65	65
Large	6.9998	0.8939	6.8097	0.7777	0.1794
<i>N</i>	66	66	66	66	66

Table D.10: Customer-size mean values and counts for routine channel shares

Customer size	Portal share	App share	OBO share	SLIMS share
Small	0.3050	0.0461	0.0221	0.1523
<i>N</i>	65	65	65	65
Medium	0.5995	0.0913	0.0300	0.1494
<i>N</i>	65	65	65	65
Large	0.5730	0.1102	0.0441	0.1631
<i>N</i>	66	66	66	66

Table D.11: Customer-size mean values and counts for support channel shares

Customer size	E-mail share	Telephone share	Portal share	Chat share
Small	0.2889	0.0529	0.0430	0.0115
<i>N</i>	65	65	65	65
Medium	0.4109	0.0833	0.0552	0.0073
<i>N</i>	65	65	65	65
Large	0.5017	0.1078	0.0621	0.0097
<i>N</i>	66	66	66	66

Table D.12: Customer-size mean values and counts for non-routine channel shares

Customer size	Incident e-mail	Incident portal	Incident tel.	Damage e-mail	Damage portal	Damage tel.
Small <i>N</i>	0.7466 29	0.0897 29	0.1552 29	0.5536 14	0.1310 14	0.3155 14
Medium <i>N</i>	0.8266 52	0.0660 52	0.0861 52	0.7196 38	0.0537 38	0.2267 38
Large <i>N</i>	0.6744 62	0.1771 62	0.1326 62	0.6813 52	0.1266 52	0.1694 52

The customer-size descriptives support the interpretation that small organisations differ most clearly from medium-sized and large organisations. Small organisations show lower dashboard activity and lower use of several structured channels, while some small organisations nevertheless display high relative dashboard intensity. This suggests a more uneven engagement pattern among smaller organisations.

Table D.13 summarises the significant post-hoc pairwise contrasts after correction for multiple testing. The table shows that the main differences are generally between small organisations and the other two size groups.

Table D.13: Summary of significant post-hoc differences between customer size classes

Indicator	Significant post-hoc pattern
Dashboard activity	large > small; medium > small; large > medium
Incidental orders per 100 orders	large > small; medium > small
App share of standard orders	large > small; large > medium; small = medium
OBO share of standard orders	large > small; medium > small; large > medium
Portal share of standard orders	large > small; medium > small
SLIMS share of standard orders	large > small; medium > small
Chat share of support tickets	large > small; large > medium; small = medium
E-mail share of support tickets	large > small; medium > small; large > medium
Portal share of support tickets	large > small; medium > small
Telephone share of support tickets	large > small; medium > small; large > medium
Damage/malfunction reports per 100 orders	large > small; medium > small

The post-hoc results clarify that customer size mainly distinguishes small organisations from the rest of the sample. Medium-sized and large organisations are more similar to one another, although differences between these two groups remain visible for some channel-use variables.

Figure D.8 provides an additional visual check of routine channel use by customer size. It supports the finding that customer size is associated with structured routine channel use. Small organisations show a wider spread and lower median portal share than medium-sized and large organisations, which is consistent with the interpretation that smaller organisations engage in a less standardised way.

**Figure D.8:** Portal share of standard orders by customer size

D.5. Supplementary location-group and country-code checks

This section reports additional contextual checks for location group and country code. These variables were explored because they may provide additional context for engagement patterns. However, both variables are less suitable as central explanatory variables than sector and customer size. Location group is based on recoded descriptors and contains an uneven distribution across categories. Country code is dominated by Dutch organisations, with only a small number of organisations in other countries.

D.5.1. Location-group check

Table D.14 reports the distribution of organisations by recoded location group. Operational locations form by far the largest group, while the other category contains only three organisations. The unknown category is also substantial. For this reason, location group is treated as an exploratory variable.

Table D.14: Distribution of organisations by recoded location group

Location group	Number of organisations
Operational	143
Unknown	30
Administrative	20
Other	3

Table D.15 reports the exploratory Kruskal-Wallis results for location group. Several engagement indicators differ significantly across location groups, especially dashboard activity, dashboard views per 100 orders, support tickets per 100 orders, and support-channel shares. However, because of the uneven distribution and the recoded nature of the variable, these results are interpreted only as exploratory support for the broader claim that engagement is context-dependent.

Table D.15: Exploratory Kruskal-Wallis results for engagement differences between location groups

Indicator	Kruskal-Wallis H	p -value
Dashboard activity	52.60	< 0.001
Dashboard views per 100 orders	46.07	< 0.001
Support tickets per 100 orders	38.54	< 0.001
Telephone share of support tickets	32.23	< 0.001
E-mail share of support tickets	30.21	< 0.001
Chat share of support tickets	25.27	< 0.001
Portal share of support tickets	23.50	< 0.001
Damage/malfunction reports per 100 orders	10.51	0.015
App share of standard orders	10.13	0.018
Portal share of standard orders	4.61	0.208
OBO share of standard orders	3.76	0.288
SLIMS share of standard orders	1.08	0.782
Incidental orders per 100 orders	0.97	0.809

The exploratory location-group results suggest that engagement differs between operational, administrative, unknown, and other location types. However, because the variable is recoded from fragmented descriptors and because group sizes are uneven, these findings are not interpreted as robust location effects in the main chapter.

D.5.2. Country-code diagnostic check

Country code was examined as an additional diagnostic context variable. Table D.16 shows that the distribution is highly uneven. Most organisations are located in the Netherlands, followed by a much smaller Belgian group. Spain and Great Britain each contain only one organisation, while 30 organisations have no available country code.

Table D.16: Distribution of organisations by country code

Country code	Number of organisations
NL	147
BE	17
Unknown	30
ES	1
GB	1

Because of this uneven distribution, country-code results are interpreted only as a diagnostic check rather than as evidence of robust cross-country differences. With a minimum group-size threshold of five organisations, only Dutch and Belgian organisations remain for comparison. With a stricter threshold of twenty organisations, fewer than two country groups remain, so no meaningful test can be performed.

Table D.17: Country-code mean values and counts for general engagement indicators

Country code	Dashboard views/100	Dashboard activity	Support/100	Incident/100	Damage/malfunction/100
BE	17.4587	0.6765	11.2561	0.8430	0.1720
<i>N</i>	16	17	16	16	16
ES	1.1395	1.0000	1.2629	0.0586	0.0117
<i>N</i>	1	1	1	1	1
GB	100.0000	0.1250	0.0000	0.0000	0.0000
<i>N</i>	1	1	1	1	1
NL	11.7359	0.7245	9.4449	0.6186	0.2653
<i>N</i>	145	147	145	145	145

Table D.18: Country-code mean values and counts for routine channel shares

Country code	Portal share	App share	OBO share	SLIMS share
BE	0.4199	0.1230	0.0310	0.0952
<i>N</i>	17	17	17	17
ES	0.7473	0.0000	0.0106	0.2421
<i>N</i>	1	1	1	1
GB	0.1250	0.0000	0.0000	0.0000
<i>N</i>	1	1	1	1
NL	0.5158	0.0920	0.0295	0.1530
<i>N</i>	147	147	147	147

Table D.19: Country-code mean values and counts for support channel shares

Country code	E-mail share	Telephone share	Portal share	Chat share
BE	0.5261	0.0330	0.0668	0.0035
<i>N</i>	17	17	17	17
ES	0.3598	0.1967	0.0415	0.0269
<i>N</i>	1	1	1	1
GB	0.0000	0.0000	0.0000	0.0000
<i>N</i>	1	1	1	1
NL	0.4336	0.1016	0.0616	0.0138
<i>N</i>	147	147	147	147

Table D.20 reports the diagnostic Kruskal-Wallis results using a minimum group size of five organisations. Under this threshold, the comparison effectively only includes the Netherlands and Belgium. The results should therefore not be interpreted as robust cross-country effects.

Table D.20: Diagnostic Kruskal-Wallis results for engagement differences by country code, minimum group size of 5

Indicator	Groups used	Kruskal-Wallis H	p -value
Telephone share of support tickets	2	16.78	< 0.001
Dashboard views per 100 orders	2	8.84	0.003
Support tickets per 100 orders	2	6.04	0.014
SLIMS share of standard orders	2	3.24	0.072
Incidental orders per 100 orders	2	3.09	0.079
E-mail share of support tickets	2	2.99	0.084
Chat share of support tickets	2	2.04	0.153
Portal share of standard orders	2	1.48	0.225
OBO share of standard orders	2	1.47	0.225
Dashboard activity	2	0.09	0.761
App share of standard orders	2	0.07	0.792
Portal share of support tickets	2	0.05	0.818
Damage/malfunction reports per 100 orders	2	0.05	0.832

The country-code diagnostics confirm that country code is not suitable as a central explanatory grouping variable in this dataset. The apparent differences between Dutch and Belgian organisations may be informative for data inspection, but the uneven group sizes and absence of sufficient observations from other countries prevent robust cross-country interpretation.

E | Supplementary quantitative results for SQ2: dashboard use and circular-performance indicators

This appendix reports supplementary descriptive statistics, missing-value checks, correlation results, group-comparison results, and exploratory regression models for SQ2. These materials support the dashboard-performance analysis reported in Chapter 7.5.

Section E.1 reports descriptive statistics and missing-value checks for the dashboard-use and circular-performance indicators. Section E.2 reports the Spearman correlation results. Section E.3 reports the dashboard-intensity group summaries and Kruskal-Wallis tests. Section E.4 reports the exploratory regression models with contextual controls.

E.1. Descriptive statistics and missing-value checks

Table E.1 reports the descriptive statistics of the dashboard engagement and circular performance indicators at the organisational level. The dashboard engagement indicators correspond to the informational dashboard engagement dimension used in Chapter 7.5.1. Relative dashboard intensity is measured as dashboard views per 100 orders, while structural dashboard activity is measured as the share of quarters in which an organisation recorded at least one dashboard view.

Table E.1: Descriptive statistics of dashboard engagement and circular performance indicators at the organisational level

Indicator	Count	Mean	Std. dev.	Min	25%	Median	75%	Max
Dashboard views per 100 orders	193	11.361	27.467	0.000	1.115	5.290	11.472	328.618
Structural dashboard activity	196	0.624	0.407	0.000	0.125	0.813	1.000	1.000
Separation percentage	182	0.738	0.210	0.073	0.657	0.789	0.900	1.000
Waste-related costs per kg	183	0.193	0.246	-1.719	0.105	0.167	0.258	1.969
CO ₂ -eq emissions per kg waste	183	1.427	0.672	-0.288	1.065	1.359	1.733	6.378

Table E.1 shows that dashboard views per 100 orders are strongly right-skewed. The median is substantially lower than the mean, while the maximum is much higher than the upper quartile. This confirms that relative dashboard intensity is shaped by a limited number of high-intensity dashboard users. Structural dashboard activity has a higher median, indicating that many organisations record dashboard activity in a substantial share of quarters, even when their relative viewing intensity remains limited.

Table E.2 reports the number and percentage of missing values. Missingness is limited for the three circular performance indicators and absent for structural dashboard activity. The analyses therefore use the available pairwise complete observations for each association.

Table E.2: Missing values for dashboard engagement and circular performance indicators

Indicator	Missing values	Missing percentage
Dashboard views per 100 orders	3	1.53
Structural dashboard activity	0	0.00
Separation percentage	14	7.14
Waste-related costs per kg	13	6.63
CO ₂ -eq emissions per kg waste	13	6.63

E.2. Spearman correlation results

Table E.3 reports the Spearman correlations between the two dashboard engagement indicators and the three circular performance indicators. Adjusted p-values are calculated using multiple-testing correction. Spearman correlations are used because several variables are skewed and contain outliers.

Table E.3: Spearman correlations between dashboard engagement and circular performance indicators

Dashboard engagement indicator	Circular performance indicator	N	Spearman ρ	p -value	Adjusted p -value	Significant
Structural dashboard activity	Waste-related costs per kg	183	-0.336	< 0.001	< 0.001	Yes
Structural dashboard activity	Separation percentage	182	0.196	0.008	0.024	Yes
Structural dashboard activity	CO ₂ -eq emissions per kg waste	183	-0.104	0.164	0.197	No
Dashboard views per 100 orders	Separation percentage	182	0.140	0.060	0.119	No
Dashboard views per 100 orders	Waste-related costs per kg	183	-0.128	0.084	0.126	No
Dashboard views per 100 orders	CO ₂ -eq emissions per kg waste	183	0.045	0.546	0.546	No

The table shows that structural dashboard activity is significantly associated with separation percentage and waste-related costs per kilogram after correction for multiple testing. Relative dashboard intensity is not significantly associated with any of the three circular performance indicators.

E.3. Dashboard-intensity group comparison

Organisations were divided into three groups based on relative dashboard intensity: low, medium, and high. Table E.4 reports the number of organisations in each group.

Table E.4: Number of organisations by dashboard-intensity group

Dashboard-intensity group	Number of organisations
Low	65
Medium	63
High	65

Table E.5 reports circular performance values by dashboard-intensity group. These results support the visual interpretation in Chapter 7.5.3: separation percentage increases gradually across dashboard-intensity groups, waste-related costs per kilogram are lowest in the medium-intensity group, and CO₂-equivalent emissions per kilogram show no clear monotonic pattern.

Table E.5: Circular performance by dashboard-intensity group

Circular performance indicator	Dashboard-intensity group	N	Mean	Median	Std. dev.
Separation percentage	Low	55	0.697	0.759	0.232
Separation percentage	Medium	63	0.744	0.790	0.200
Separation percentage	High	64	0.768	0.821	0.195
Waste-related costs per kg	Low	56	0.241	0.206	0.149
Waste-related costs per kg	Medium	63	0.158	0.162	0.144
Waste-related costs per kg	High	64	0.186	0.160	0.363
CO ₂ -eq emissions per kg waste	Low	56	1.518	1.396	0.805
CO ₂ -eq emissions per kg waste	Medium	63	1.375	1.303	0.592
CO ₂ -eq emissions per kg waste	High	64	1.399	1.443	0.619

To test whether the observed descriptive differences are statistically meaningful, Kruskal-Wallis tests were conducted. Table E.6 reports the results. None of the tests remain significant after correction for multiple testing.

Table E.6: Kruskal-Wallis tests for differences in circular performance between dashboard-intensity groups

Circular performance indicator	Groups compared	Kruskal-Wallis H	p -value	Adjusted p -value	Significant
Separation percentage	Low, Medium, High	3.815	0.148	0.223	No
Waste-related costs per kg	Low, Medium, High	7.875	0.019	0.058	No
CO ₂ -eq emissions per kg waste	Low, Medium, High	1.627	0.443	0.443	No

Because none of the Kruskal-Wallis tests remained significant after correction for multiple testing, no pairwise post-hoc tests were performed.

E.4. Exploratory regression models with contextual controls

Table E.7 reports exploratory regression models of circular performance on dashboard engagement, controlling for sector cluster and customer size. These models are not interpreted causally. They are included as robustness checks to examine whether the bivariate dashboard-performance associations remain visible after accounting for basic organisational context.

Table E.7: Exploratory regression models of circular performance on dashboard engagement, controlling for sector cluster and customer size

Circular performance indicator	Dashboard engagement predictor	N	Coefficient	<i>p</i> -value	<i>R</i> ²	Adjusted <i>p</i> -value
Waste-related costs per kg	Structural dashboard activity	159	-0.088	0.171	0.138	0.514
Waste-related costs per kg	Dashboard views per 100 orders	159	0.0004	0.904	0.132	0.990
CO ₂ -eq emissions per kg waste	Dashboard views per 100 orders	159	-0.0013	0.817	0.150	0.990
CO ₂ -eq emissions per kg waste	Structural dashboard activity	159	-0.0022	0.990	0.147	0.990
Separation percentage	Structural dashboard activity	159	0.142	0.083	0.111	0.496
Separation percentage	Dashboard views per 100 orders	159	0.0016	0.438	0.128	0.877

None of the dashboard engagement predictors remain statistically significant after correction for multiple testing. The positive coefficient for structural dashboard activity in the separation-percentage model and the negative coefficient for structural dashboard activity in the waste-related-costs model are substantively consistent with the bivariate results, but they are not statistically robust in the controlled specification.

F | Interview selection frame and realised sample

This appendix provides supplementary information on the construction of the interview-selection frame, the filtered candidate pool, the realised interview sample, and the anonymisation of interviewed organisations. These materials support the qualitative research design described in Chapter 8.

Section F.1 documents the construction of the organisation-level selection frame. Section F.2 reports the filtered candidate pool used for interview recruitment. Section F.3 provides additional checks on broader engagement variation in the realised interview sample. Section F.4 describes the anonymisation of interviewed organisations.

F.1. Construction of the selection frame

The interview-selection frame was constructed by aggregating the integrated company-quarter dataset to the organisational level. The dataset covered 196 unique organisations. For each organisation, mean values were calculated for the main dashboard-use indicators, circular-performance indicators, and additional engagement indicators. Contextual descriptors such as sector and customer size were retained at the organisational level.

Relative dashboard intensity was measured as the average number of dashboard views per 100 orders. Structural dashboard activity was measured as the average of the quarterly binary dashboard-activity indicator, representing the share of quarters in which at least one dashboard view was recorded. Dashboard intensity was divided into low, medium, and high groups using tertile-based categorisation. Structural dashboard activity was grouped into four categories: never active, occasionally active, regularly active, and always active. These two indicators were then combined into an informational dashboard engagement profile.

Circular performance was operationalised through separation percentage and waste-related costs per kilogram. A higher separation percentage was treated as better performance. The cost indicator was reversed so that lower waste-related costs per kilogram corresponded to better performance. These two indicators were combined into an overall circular-performance profile. CO₂-equivalent emissions per kilogram were retained descriptively in the selection overview, but were not used to construct the primary performance profile.

Table F.1 reports the distribution of interview case types before applying additional selection restrictions. The classification is based on the combination of the informational dashboard engagement profile and the circular-performance profile.

Table F.1: Distribution of interview case types before additional selection restrictions

Interview case type	Number of organisations
Mixed/intermediate	104
High engagement / High performance	28
High engagement / Low performance	23
Low engagement / Low performance	22
Not classified due to missing profile information	14
Low engagement / High performance	5
Total	196

The distribution shows that the majority of organisations fall into the mixed/intermediate category. Among the contrasting case types, high engagement/high performance, high engagement/low

performance, and low engagement/low performance cases are present in sufficient numbers before filtering. Low engagement/high performance cases are empirically rare.

F.2. Filtered candidate pool

For the interview recruitment process, additional restrictions were applied. Organisations were retained only if they had a known sector classification and observable dashboard presence. Table F.2 reports the resulting candidate pool for the main contrast categories.

Table F.2: Filtered candidate pool by interview case type

Interview case type	Number of candidate organisations
High engagement / High performance	27
High engagement / Low performance	23
Low engagement / Low performance	7
Low engagement / High performance	1
Total main contrast categories	58

The filtered candidate pool confirms that the contrast categories were not equally available. In particular, low engagement/high performance cases were rare after applying the restrictions. This explains why the realised interview sample could not be perfectly balanced across all four main contrast types.

F.3. Variation across broader engagement indicators

To check whether the realised interview sample also reflected broader multidimensional engagement patterns, additional engagement indicators were inspected for the interviewed organisations. Table F.3 reports the observed range of selected broader engagement indicators within the realised sample.

Table F.3: Observed range of broader engagement indicators in the realised interview sample

Indicator	Minimum	Maximum
Support interactions per 100 orders	0.000	59.519
Incidental orders per 100 orders	0.000	1.090
Damage/malfunction reports per 100 orders	0.000	0.764
Portal share of routine standard orders	0.000	0.965

The realised interview sample varies not only in informational dashboard engagement and circular performance, but also in support-related engagement, routine transactional engagement, and non-routine operational engagement. This supports the use of the interviewed organisations as analytically informative cases for the qualitative phase.

F.4. Anonymisation of interviewed organisations

Company names used during the internal recruitment and selection process are not reported as identifiable case labels. In the interview analysis, organisations are anonymised to protect confidentiality. Where relevant, cases are described by interview case type, sector, and customer-size category rather than by company name.

G | Informed consent form

This appendix presents the informed consent form used for the interview phase of this research. Participants received this information before taking part in the interview and were asked to provide consent for participation, audio recording, transcription, and the use of anonymised responses or quotations in research outputs.

Delft University of Technology

Informed consent form

Opening statement

You are being invited to participate in a research study titled:

“Unlocking Digital Circularity: Socio-Technical Conditions Shaping Organisational Engagement with Digital Circular-Economy Platforms.”

This study is being conducted by Suus Plum, MSc student in Engineering and Policy Analysis at Delft University of Technology (TU Delft), under supervision of Dr. Anneke Zuiderwijk and Dr. Jan Anne Annema. The research is conducted in collaboration with Milgro, a Dutch business-to-business service provider in waste management and circular-economy reporting.

The purpose of this research study is to examine how organisations engage with a digital circular-economy platform and how such engagement relates to circular performance outcomes. The study aims to better understand how digital performance dashboards are used in practice and what organisational factors influence their effective use.

Participation will take approximately 45–60 minutes. The data will be used for the completion of a TU Delft Master’s thesis and may contribute to academic publications or conference presentations. The data will not be used for commercial purposes.

During the interview, you will be asked questions about:

- your experience using the Milgro platform;
- how you use performance dashboards;
- how platform data is embedded in organisational routines;
- organisational factors influencing platform engagement.

The following data may be collected:

- your name and email address, for scheduling and consent purposes only;
- your professional role and sector;
- an audio recording of the interview, for transcription purposes.

The interview will be recorded and transcribed. Transcripts will be pseudonymised, and direct identifiers such as names and company identifiers will be removed where possible.

Your responses will remain confidential to the best of our ability. As with any digital data storage or online communication, there is a minimal risk of a data breach. Data will be stored securely on TU Delft’s protected servers, accessible only to the researcher and TU Delft supervisors. Findings will be reported in anonymised or aggregated form. Individual responses will not be shared with Milgro. This study does not involve open public data archiving of interview data.

Personally identifiable information, such as names and contact details, will be deleted within one month after completion of the study, no later than the end of July 2026. Pseudonymised research data, including interview transcripts and thematic analysis files, will be securely stored for up to one year

after project completion for validation and assessment purposes, after which it will be permanently deleted.

Your participation in this study is entirely voluntary and you can withdraw at any time without giving a reason. You are free to decline to answer any question. You may withdraw from the study and request deletion of your data up until the start of data analysis, anticipated to begin approximately one week after the interview.

If a scientific article is written based on this research, pseudonymised research data may be used for follow-up academic publications or educational purposes within the domain of digital circular economy and organisational platform engagement. You will remain anonymous in all outputs.

Consent statement

I have read and understood the information provided above. I have had the opportunity to ask questions. I voluntarily agree to participate in this study and consent to the personal data processing described above.

I agree that my anonymised responses or quotations may be used in research outputs.

Name of participant: _____

Signature: _____

Date: _____

H | Semi-structured interview guide

This appendix presents the consolidated semi-structured interview guide used for the qualitative part of this research. The interviews followed the same overall structure, but the exact wording and emphasis of questions were adapted to the respondent's role, the organisation's use of the Milgro platform, and the case-selection profile. For example, some interviews placed more emphasis on dashboard use and circular-performance improvement, while others focused more strongly on alternative routines, limited platform use, or operational waste-management practices.

A. Opening and respondent role

1. Could you briefly describe your function and responsibilities within the organisation?
2. To what extent are you involved in waste management, circularity, reporting, monitoring, or the Milgro platform?
3. Who within the organisation normally works with the Milgro platform, dashboards, waste data, or waste-related reports?
4. Is waste management or platform use mainly assigned to one person or department, or is it spread across multiple departments, locations, or operational teams?

B. General use of the Milgro platform

5. Could you describe how the organisation generally uses the Milgro platform?
6. Which parts of the platform are used most frequently?
7. Which parts of the platform are used rarely or not at all?
8. At what moments is the platform mainly used? For example, for fixed reports, operational questions, audits, evaluations, deviations, management meetings, or ad hoc issues.
9. Does the platform have a fixed place in existing work processes, or is it mainly consulted when a specific issue arises?

C. Dashboard use and perceived value

10. How are the dashboards used within the organisation: by whom, how often, and for what purpose?
11. Which dashboard information is considered most useful, and why?
12. For which decisions, actions, reports, or internal discussions is dashboard information used?
13. To what extent is the dashboard information concrete enough to support decision-making or action?
14. Can you give an example in which dashboard information led to an action, decision, or internal discussion?
15. Can you also give an example in which dashboard information was available, but did not lead to action?
16. Are there dashboard elements that are less useful or less relevant? If so, what explains this?

D. Routines, ownership, and follow-up

17. Is dashboard use embedded in fixed work processes or meetings, such as monthly reports, KPI discussions, production meetings, management updates, sustainability meetings, quality meetings, or location meetings?

18. Who is responsible for monitoring and following up on waste and circularity figures? Is this formally assigned?
19. What happens when figures deviate from expectations?
20. Who is able to take action when such deviations occur?
21. Are improvement measures based on dashboard information followed up? If so, how?
22. How is information from the dashboard translated to the operational work floor or relevant departments?

E. Organisational conditions and barriers

23. What helps the organisation to use the platform and dashboard effectively?
24. What sometimes hinders the use of the platform or the follow-up of dashboard information?
25. Does the use of digital waste information fit well within existing work processes, or does it feel like an additional task alongside regular work?
26. What role do management or supervisors play in the use of waste and circularity information?
27. Is waste and circularity information actively discussed for improvement, or mainly registered and reported?

F. External dependencies and sector-specific conditions

28. To what extent is the organisation dependent on other parties or departments to improve waste or circularity performance?
29. Does the organisation have sufficient influence to implement improvements based on dashboard information? Why or why not?
30. Are there sector-specific factors that influence waste separation or circularity?
31. Do external requirements or targets play a role in how the platform is used?

G. Case-specific follow-up questions

Depending on the case-selection profile, additional follow-up questions were asked. These questions were not used as a fixed questionnaire, but as prompts to explore the mechanisms behind the observed quantitative patterns.

High dashboard engagement and relatively favourable circular performance

32. The available data suggest that the organisation makes relatively active use of dashboards and performs relatively favourably on circular-performance indicators. Do you recognise this pattern?
33. What makes dashboard information practically usable within the organisation?
34. Which routines, responsibilities, or ways of working ensure that information is not only viewed, but also followed up?
35. Why does the organisation succeed, or not succeed, in translating dashboard information into improvement actions?
36. Do you think dashboard use has contributed to performance indicators such as separation rate, waste costs, or circularity goals? Why or why not?

Limited dashboard engagement or alternative performance routes

37. If the dashboard is not central in daily work, how are waste and circularity performance monitored instead?
38. Which other information sources are used alongside or instead of the Milgro platform?
39. Which routines or agreements help the organisation to manage waste separation, costs, or circularity without intensive dashboard use?

40. Are good waste or circularity outcomes mainly dependent on digital monitoring, or more on practical agreements and routines?

H. Closing questions

41. If you could improve one thing about the dashboard, the platform, or the support around it, what would it be?
42. Is there anything I have not asked, but that is important for understanding how the platform works in practice within your organisation?
43. May I contact you later for a short clarification question if needed?

I | Qualitative codebook and cross-organisation comparison

This appendix documents the qualitative codebook used to analyse the interview transcripts, as described in Chapter 8.6. The codebook combines deductive codes derived from the analytical framework and qualitative sub-questions with inductive codes that emerged during the analysis.

The appendix also reports the cross-organisation comparison tables used during the qualitative synthesis in Chapter 9. These tables served as an intermediate analytical step between transcript coding and the thematic interpretation presented in the qualitative results chapter.

I.1. Qualitative codebook

The interview transcripts were coded using ten code families. The first four code families primarily relate to SQ3 and capture how organisations use dashboard and platform information, how respondents evaluate the usefulness of this information, which data limitations they experience, and whether dashboard information becomes connected to action, investigation, discussion, or improvement. The next five code families primarily relate to SQ4 and capture organisational embedding, ownership and responsibility, barriers, sector and contextual conditions, and external dependencies. A final inductive code family was used to capture recurring patterns that emerged during coding.

Table I.1: Overview of qualitative code families

Code family	Analytical focus
SQ3 – Dashboard and platform use	How dashboard or platform information is used in practice, including reporting, monitoring, control, operational steering, and ad hoc use.
SQ3 – Perceived usefulness	How respondents evaluate the usefulness of dashboard or platform information, including insight, accessibility, standardisation, and reporting efficiency.
SQ3 – Actionability	Whether and how dashboard information leads to action, investigation, discussion, business cases, awareness, or improvement.
SQ3 – Data limitations	Limitations related to timing, completeness, coverage, definitions, granularity, visibility, and methodological transparency.
SQ4 – Organisational embedding	The extent to which dashboard use is embedded in routines, meetings, reporting cycles, management processes, and operational work.
SQ4 – Ownership and responsibility	How responsibility for monitoring, interpretation, decision-making, and follow-up is distributed across roles and departments.
SQ4 – Barriers	Organisational and practical barriers that limit dashboard use or the translation of information into action.
SQ4 – Sector and contextual conditions	Sector-specific and operational conditions that shape dashboard use and circular-performance improvement.
SQ4 – External dependencies	Dependencies on suppliers, customers, processors, contractors, regulation, auditors, corporate requirements, or Milgro.
IND – Emergent codes	Inductive codes capturing recurring themes that emerged during coding, such as provider-supported contextual translation and alternative internal routines.

I.1.1. SQ3 - Dashboard and platform use

This code family captures how organisations use dashboard and platform information in practice.

Table I.2: Codes for dashboard and platform use

Code	Description
Dashboard use for reporting	Dashboard data are used for annual reports, ESG, CSRD, ISO, customer reporting, corporate reporting, or audit-related reporting.
Dashboard use for monitoring	Dashboard data are used to monitor waste streams, costs, separation percentages, CO ₂ impact, or trends.
Dashboard use for KPI monitoring	Dashboard data are linked to specific performance indicators or internal KPIs.
Dashboard use for operational steering	Dashboard information is used to adjust operational processes or waste practices.
Dashboard use for strategic decision-making	Dashboard information supports strategic decisions, investments, business cases, or long-term choices.
Dashboard use for control	Dashboard data are used to check invoices, orders, costs, completed services, or operational records.
Dashboard use for investigation	Dashboard data are used to investigate deviations, anomalies, or unexpected patterns.
Dashboard use for pilot evaluation	Dashboard data are used to design, support, monitor, or evaluate a pilot or improvement project.
Platform use for operational process	The platform is used for operational processes such as waste collection requests, order placement, damage reports, or document retrieval.
Document retrieval	The platform is used to retrieve documents such as freight documents, weighing slips, invoices, or transport documents.
Data export/manual processing	Data are exported from the platform and processed manually in Excel or another internal system.
Selective dashboard use	Only specific dashboard modules or functionalities are used, while others are ignored or rarely consulted.
Ad hoc dashboard use	The dashboard is consulted only when a question, issue, reporting need, or deviation occurs.
Ad hoc platform use	The platform is used only when a specific operational event occurs, such as an additional collection request, support question, container issue, or incident, rather than as part of regular monitoring or dashboard-based routines.
Periodic dashboard use	The dashboard is used at recurring moments, such as monthly, quarterly, or annually.
No dashboard use	The organisation does not use the dashboard.
No platform use	The organisation does not use, or hardly uses, the platform.

I.1.2. SQ3 - Perceived usefulness

This code family captures how respondents assess the usefulness or value of dashboard and platform information.

Table I.3: Codes for perceived usefulness

Code	Description
Perceived usefulness	The respondent explicitly describes dashboard or platform information as useful, valuable, or helpful.
Dashboard provides insight	The dashboard makes waste streams, costs, volumes, impact, or locations more visible or understandable.
Data visibility	The dashboard makes data visible that were previously fragmented, unclear, or difficult to access.
Data accessibility	Dashboard or platform data are easier to retrieve than through separate files, invoices, e-mails, or internal records.
Reporting efficiency	The dashboard reduces administrative work or improves efficiency in reporting processes.
Data standardisation	The dashboard supports consistent data collection, calculation, or reporting across locations or entities.
Location-level insight	The dashboard makes differences between locations visible.
Waste balance use	The waste balance is used or described as a valuable dashboard component.
CO ₂ reporting use	CO ₂ information is used or considered valuable for reporting or monitoring.
Separation performance insight	Separation percentage or waste-separation performance is used or considered relevant.
Waste destination insight	The dashboard provides insight into waste destination, such as recycling, incineration, animal feed, or other processing routes.
Cost insight	Cost information is used or considered useful.
Trust in data	The respondent expresses trust in the dashboard or platform data.
Ease of understanding	The dashboard is described as understandable, accessible, or easy to interpret.
Data sufficiency	The respondent indicates that the available dashboard or platform data are sufficiently complete, detailed, or useful for the intended purpose.
Dashboard as supporting tool	The dashboard is described as a useful supporting tool, but not as a leading steering instrument.
Dashboard contribution potential	The respondent indicates that the dashboard could become more valuable if better embedded, improved, or used more actively.

I.1.3. SQ3 - Actionability

This code family captures whether dashboard information leads to action, investigation, discussion, or improvement.

Table I.4: Codes for actionability

Code	Description
Actionability	Dashboard information is sufficiently concrete or relevant to support action.
Dashboard triggers action	Dashboard information directly leads to an action, intervention, correction, or improvement measure.
Dashboard triggers investigation	Dashboard information leads to further investigation or internal questioning.
Dashboard triggers discussion	Dashboard information leads to internal discussion or discussion with Milgro.
Dashboard triggers awareness	Dashboard information creates awareness about waste streams, costs, impact, or improvement potential.
Dashboard supports business case	Dashboard information supports a business case, investment decision, or financial argument.
Dashboard use for improvement	Dashboard information is used to identify or support improvement opportunities.
Dashboard provides insight, not direct action	Dashboard information creates insight but does not directly lead to operational action.
Limited actionability	Dashboard information is insufficiently concrete, timely, relevant, or actionable for direct follow-up.
Limited short-term actionability	Dashboard information is useful for longer-term monitoring but not for short-term or day-to-day steering.
Dashboard available but delayed action	Relevant dashboard information was available, but action was delayed or not followed up in time.
No dashboard-triggered action	No concrete action could be identified as resulting from dashboard information.
Dashboard not used by action-takers	Dashboard information is mainly accessed by people who do not directly control the operational processes needed for follow-up.
Limited dashboard contribution	The dashboard contributes only weakly or indirectly to performance improvement.

I.1.4. SQ3 - Data limitations

This code family captures limitations in the dashboard data, including timing, completeness, definitions, coverage, and granularity.

Table I.5: Codes for data limitations

Code	Description
Data timeliness problem	Data are delayed, not available in time, or lag behind operational events.
Data completeness problem	Data are incomplete at the moment they are needed.
Data coverage limitation	Not all relevant sites, entities, waste streams, or processes are included in the platform data.
Reporting risk	Data limitations create risks for reporting reliability, completeness, or auditability.
Data reliability over time	Data may change, be corrected, or become more reliable only after a later update.
Data granularity limitation	Data are not detailed enough for the relevant department, process, site, line, shop, or waste stream.
Waste stream classification issue	Waste streams are unclear, misclassified, or interpreted differently by users.
Definition mismatch	Dashboard definitions do not fully align with internal policy definitions, reporting categories, or organisational concepts.
Need for contextual interpretation	Dashboard data require operational or contextual knowledge to be interpreted correctly.
Limited data visibility	Relevant data are not visible enough, are difficult to find, or are hidden in the system.
Missing alerts	The dashboard lacks automatic alerts, pop-ups, notifications, or proactive signals.
Need for trend comparison	The respondent needs better comparison across months, quarters, years, or locations.
Methodological transparency issue	The calculation method, especially for CO ₂ or impact, is insufficiently clear to the user.
CO ₂ calculation uncertainty	There is uncertainty about emission factors, CO ₂ calculations, or impact methodology.
Platform scope limitation	The platform does not cover all relevant locations, processes, waste streams, or organisational entities.
Dashboard improvement suggestion	The respondent proposes a concrete dashboard or platform improvement.
AI/proactive recommendation need	The respondent expresses a need for AI, proactive recommendations, alerts, or automated interpretation.

I.1.5. SQ4 - Organisational embedding

This code family captures how dashboard use is embedded in organisational routines, reporting cycles, meetings, and operational processes.

Table I.6: Codes for organisational embedding

Code	Description
Embedded reporting routine	Dashboard data are part of a recurring reporting process.
Embedded management routine	Dashboard data are discussed in management meetings, plant teams, QBRs, or management reviews.
Embedded operational routine	Platform or dashboard use is part of daily or recurring operational work.
Embedded in existing process	Dashboard or platform use is integrated into an existing organisational process.
Partial embedding	Dashboard use is embedded in some routines but not in others.
Lack of embedded routine	Dashboard use has no fixed place in routines, meetings, or work processes.
Lack of management routine	Dashboard information is not structurally discussed in management meetings.
No meeting routine	Dashboard information is explicitly not discussed in recurring meetings.
Reporting cycle	Dashboard use follows monthly, quarterly, annual, or other reporting cycles.
Annual review	Dashboard information is used in an annual review or annual meeting.
Periodic Milgro review	Dashboard information is mainly discussed during periodic meetings with Milgro.
QBR routine	Dashboard information is used in quarterly business reviews or customer review meetings.
Plant team routine	Dashboard information is discussed in plant-team or production-management routines.
Action register	Improvement actions are documented in an action list or action register.
Follow-up routine	There is a recurring process for following up on dashboard information or improvement actions.
Lack of formal routine	Follow-up is not formally organised or process-based.
Informal follow-up	Follow-up occurs informally through ad hoc communication or individual initiative.
Intended future embedding	The organisation intends to embed dashboard use more structurally in the future.
Work-floor communication	Dashboard insights or waste instructions are translated to the work floor.
Central-local translation gap	Dashboard information remains centralised and is insufficiently translated to locations or operational teams.

I.1.6. SQ4 - Ownership and responsibility

This code family captures how responsibility for dashboard use, interpretation, and follow-up is distributed.

Table I.7: Codes for ownership and responsibility

Code	Description
Role and responsibility	General description of respondent role or organisational responsibility.
Formal ownership	Responsibility for monitoring or follow-up is formally assigned.
Informal ownership	Responsibility is implicit, informal, or dependent on individual initiative.
Lack of formal ownership	No formal owner is assigned for monitoring or follow-up.
Fragmented ownership	Responsibility is spread across multiple departments, roles, or organisational levels.
Distributed responsibility	Multiple roles or departments are involved in dashboard use, waste management, or follow-up.
Monitoring-action split	One actor monitors dashboard information while another actor must implement action.
Operational ownership	Operational teams, site managers, or local managers are responsible for action.
Operational ownership gap	Operational responsibility is unclear, weak, or not sufficiently taken up.
Role ambiguity	It is unclear who is responsible for interpretation, decision-making, or follow-up.
Role clarity	Roles and responsibilities are clearly assigned.
Role concentration	Dashboard use or interpretation is concentrated in one or a few individuals.
Centralised dashboard use	Dashboard use is mainly performed by central staff or central departments.
Distributed platform use	Platform use is distributed across operational users or locations.
Sustainability role	Sustainability staff use, interpret, or report dashboard information.
ESG role	ESG staff use dashboard information for group-level reporting or analysis.
HSEQ/QHSE/KAM role	HSEQ, QHSE, KAM, or similar functions are responsible for dashboard use or waste-related monitoring.
Facility role	Facility management is responsible for waste processes or platform use.
Finance involvement	Finance, accounting, or audit-related functions use or request dashboard data.
Management attention	Management asks for, discusses, or acts on dashboard information.
Limited management attention	Management attention for dashboard use or waste performance is limited.
Accountability routine	Actors are held accountable for dashboard figures, KPIs, or follow-up actions.

I.1.7. SQ4 - Barriers

This code family captures barriers that limit dashboard use, actionability, or circular-performance improvement.

Table I.8: Codes for barriers

Code	Description
Priority constraint	Waste, dashboard use, or circularity has limited priority compared with other tasks.
Time constraint	There is insufficient time to analyse dashboard information or follow up on it.
Capacity constraint	There is insufficient personnel or organisational capacity for dashboard use or follow-up.
Customer size constraint	Organisational scale limits the ability to assign a dedicated role or routine.
Lack of dedicated role	No dedicated role exists for waste monitoring, dashboard use, or follow-up.
Extra task perception	Dashboard use is perceived as an additional task rather than part of normal work.
Tool fatigue	Users experience the platform as another additional digital tool.
Limited perceived need	The organisation does not perceive a strong need to use the dashboard more actively.
Operational pressure	Daily operational demands crowd out dashboard use or improvement work.
Core business priority	The organisation's primary task receives priority over waste or circularity improvement.
Financial constraint	Costs or budget limitations constrain improvement actions.
Investment barrier	Improvement requires an investment that is difficult to justify or approve.
Space constraint	Physical space limitations constrain waste separation or improvement.
Operational feasibility constraint	Practical operational conditions make an improvement difficult to implement.
Cultural barrier	Organisational culture, habits, or attitudes reduce attention to waste improvement.
Behavioural barrier	Employee behaviour limits waste separation or improvement.
Weak accountability	No actor is clearly held responsible for dashboard-based follow-up.
Weak process embedding	Follow-up is not structurally embedded in organisational processes.
Delayed follow-up	Follow-up occurs too late or after a missed opportunity.
Data discipline variation	Data registration or process discipline differs between teams, departments, or locations.
Diminishing returns	Additional improvement is perceived as increasingly costly or limited in effect.

I.1.8. SQ4 - Sector and contextual conditions

This code family captures sector-specific and operational conditions that shape dashboard use and circular-performance improvement.

Table I.9: Codes for sector and contextual conditions

Code	Description
Food-specific constraints	Food-sector conditions such as food safety, category 2/3 material, organic waste, or production planning influence waste management.
Food safety constraint	Food safety, hygiene, contamination risk, or product requirements constrain circular options.
Organic waste stream	Organic residual streams such as food residues, animal-feed streams, or category 3 material are relevant.
Production planning dependency	Waste management depends on production planning or production variability.
Packaging constraint	Packaging materials or packaging requirements limit waste separation or recycling.
Retail-specific constraints	Retail context, store structure, distribution centres, or store-level processes affect waste management.
Retail traceability limitation	Waste data cannot be traced sufficiently to individual stores or retail locations.
Mobility-specific constraints	Mobility, automotive, repair-shop, or transport-related conditions influence waste management and circular-performance improvement, for example vehicle parts, bumpers, paint tins, hazardous materials, workshop routines, packaging from car parts, or limited space for separate waste containers.
Education-specific constraints	Education-sector conditions, such as student behaviour, canteen or aula waste practices, school-location routines, and limited control over waste separation by pupils or students, influence waste management and circular-performance improvement.
Healthcare-specific constraints	Healthcare protocols, patient safety, hygiene, or medical waste complexity influence waste management.
Hygiene/safety constraint	Hygiene, safety, or health requirements limit waste separation or circularity.
Infrastructure-specific constraints	Infrastructure assets, maintenance work, project sites, or technical systems shape waste generation.
Project-location complexity	Waste arises at temporary, dispersed, or project-based locations.
Logistics-specific constraints	Warehousing, transport, container use, fill rates, pallets, or logistics processes shape waste management.
Warehouse waste streams	Warehouse-specific waste streams such as pallets, wood, packaging, or metal are relevant.
OV/maintenance context	Public-transport, maintenance, workshop, or technical-service context shapes waste streams.
Industry-specific constraints	Industrial or plant-specific processes shape waste streams and improvement opportunities.
Hazardous waste stream	Hazardous waste streams affect costs, handling, classification, or operational routines.
Waste stream volatility	Waste streams fluctuate strongly because of production, incidents, projects, or batch processes.
Stable waste streams	Waste streams are relatively stable and predictable.
Limited operational complexity	Waste streams are relatively simple or operationally predictable.
Multi-site complexity	Multiple locations, factories, sites, or entities complicate data interpretation and follow-up.
Organisational complexity	Organisational size, structure, departments, or governance complicate dashboard use and actionability.

I.1.9. SQ4 - External dependencies

This code family captures dependencies on actors, requirements, or conditions outside the immediate dashboard user group.

Table I.10: Codes for external dependencies

Code	Description
Supplier dependency	Improvement depends on suppliers or upstream supply-chain actors.
Dependency on contractors	Improvement depends on contractors or project partners.
Dependency on processors	Improvement depends on waste processors or treatment partners.
Dependency on transporters	Improvement depends on waste transporters or logistics partners.
Recycler dependency	Improvement depends on whether recyclers accept the material.
External market constraint	Market conditions limit recycling, reuse, or valorisation opportunities.
Customer reporting pressure	Customers request waste, circularity, or sustainability information.
Corporate reporting pressure	Corporate headquarters or group-level requirements drive reporting.
Investor reporting pressure	Investors request or influence sustainability, carbon, or waste reporting.
Regulatory pressure	Regulation or expected regulation increases the need for dashboard data or circularity action.
CSRD pressure	CSRD or CSRD-like reporting expectations increase data needs.
ISO reporting	ISO 14001 or similar standards drive data use or reporting.
Audit pressure	Accountants, auditors, or assurance processes require data or evidence.
External regulatory pressure	Specific external rules, permits, sector regulations, or authorities influence waste management.
Supply-chain collaboration	Improvement requires collaboration with supply-chain actors.
Packaging regulation	Packaging regulation or packaging-related obligations affect waste decisions.
External expertise need	The organisation needs external expertise to interpret data or identify improvement options.
Shared responsibility with Milgro	Improvement or follow-up is carried out together with Milgro.
Dependency on Milgro	The organisation depends on Milgro for data, interpretation, advice, or follow-up.

I.1.10. IND - Emergent codes

This code family captures inductive patterns that emerged during coding and were used to refine the cross-case interpretation.

Table I.11: Inductive codes

Code	Description
Provider-supported contextual translation	Milgro helps interpret dashboard data and translate it into possible actions.
Milgro as advisor	Milgro is perceived as an expert or advisory partner.
Milgro relationship quality	The quality of communication, contact persons, or relationship with Milgro affects dashboard use or follow-up.
Alternative internal routines	The organisation uses internal routines outside the dashboard to monitor or manage waste.
Alternative data source	Freight documents, invoices, internal systems, Excel sheets, or other data sources replace or complement dashboard data.
Alternative communication channels	Telephone, e-mail, or direct contact replace platform-based communication.
Alternative reporting system	Another reporting system is used alongside or instead of the Milgro platform.
Internal interpreter	An internal actor translates dashboard information into organisationally relevant language or action.
Dashboard as legitimacy source	Dashboard information or Milgro expertise helps legitimise an issue internally.
Reporting embedded but operationally weak	Dashboard data are well embedded in reporting but weakly embedded in operational steering.
Insight-action gap	Dashboard information creates insight, but action remains limited, delayed, or absent.
High engagement does not imply embedded use	High dashboard engagement does not necessarily mean dashboard information is embedded in routines or action.
Low engagement does not imply no monitoring	Low dashboard engagement does not necessarily mean that the organisation lacks monitoring or follow-up.
Dashboard fit with operational speed	The platform or dashboard fits, or fails to fit, the speed required by operational processes.
Data needs process knowledge	Dashboard data are only meaningful when interpreted with knowledge of local processes.

I.2. Cross-organisation comparison

Tables I.12 and I.13 summarise the within-organisation memos and compare the interviewed organisations across the main analytical dimensions used in the qualitative analysis. Company names are omitted to preserve anonymity. The comparison is split into two tables to improve readability.

Table I.12 reports the organisational profile and dominant dashboard or platform use. Table I.13 reports actionability, organisational embedding, ownership, barriers, and the main interpretation. The tables served as an intermediate analytical step between transcript coding and the thematic interpretation presented in Chapter 9. They are not intended as quantitative scoring tables, but as qualitative comparisons of recurring mechanisms across engagement-performance profiles.

Table I.12: Cross-organisation comparison of qualitative interview findings: organisational profile and platform use

Organisation	Engagement-performance profile	Sector	Size	Main dashboard/platform use	Perceived usefulness
Interviewed organisation 1	High engagement / High performance	Food	Medium	Dashboard used for waste-flow analysis, trends, valuation, costs, and reporting.	High; dashboard provides strategic insight into waste optimisation and valorisation.
Interviewed organisation 2	High engagement / High performance	Retail	Large	Used for reporting, audits, pilots, supply-chain insight, sustainability reporting, and selected waste-separation projects.	High; dashboard centralises fragmented waste information and supports translation across departments.
Interviewed organisation 3	High engagement / High performance	Food	Large	Used mainly for carbon calculations, CSRD/ESG reporting, investor reporting, and data exports.	High for reporting and standardisation across factories.
Interviewed organisation 4	High engagement / High performance	Food	Large	Used for monthly KPI reporting, rest-waste monitoring, animal-feed flows, management information, and order placement.	High; reports are directly useful for KPIs, accountant questions, and management information.
Interviewed organisation 5	High engagement / High performance	Logistics	Large	Used for monthly reports, customer reporting, container calls, QPR/QBR meetings, and Excel exports.	High; useful for customer accountability, waste-stream insight, and logistics improvement.
Interviewed organisation 6	High engagement / Low performance	Healthcare	Large	Used for sustainability reporting, CSRD exports, waste-flow overview, documentation, and internal fact-checking.	High for reporting, but limited for direct operational steering.
Interviewed organisation 7	High engagement / Low performance	Mobility	Small	Used locally for operational order placement and support questions.	High for simple operational tasks.
Interviewed organisation 8	High engagement / Low performance	Mobility	Large	Used centrally for CSRD, CO ₂ footprinting, validation, branch comparison, and awareness creation.	Very high centrally; dashboard is valuable for insight and data validation.
Interviewed organisation 9	High engagement / Low performance	Construction & Industry	Large	Used for CO ₂ reporting, annual reporting, Milgro meetings, and location-level insight.	High; dashboard is considered useful and clear.
Interviewed organisation 10	Low engagement / High performance	Food	Medium	Milgro dashboard is hardly used; monitoring occurs through freight notes, internal systems, and own monthly overviews.	Low for the Milgro platform, but high for internal routines.
Interviewed organisation 11	Low engagement / Low performance	Construction & Industry	Small	App used for orders; dashboard used incidentally for customer questions and ISO reporting.	Medium for reporting, limited as improvement tool.
Interviewed organisation 12	Low engagement / Low performance	Logistics	Medium	Mainly uses e-mail, Excel, invoices, phone calls, and direct contact; limited platform use.	Potentially useful, but not yet realised in practice.
Interviewed organisation 13	Mixed/intermediate	Construction & Industry	Medium	Used for monitoring, reporting, separation percentage, CO ₂ , costs, and operational calls.	High; especially useful for long-term monitoring and reporting.
Interviewed organisation 14	Mixed/intermediate	Government	Large	Used for operational container orders; no dashboard access at respondent level.	Low–medium; sufficient for basic orders but limited in broader value.
Interviewed organisation 15	Mixed/intermediate	Logistics	Medium	Used for quarterly, ISO, and CO ₂ reporting.	Medium; useful as information source.
Interviewed organisation 16	Mixed/intermediate	Infra & Energy	Large	Used for contract management, order checks, cost control, incident analysis, and operational order placement.	Medium–high for contract and cost control.

Table I.13: Cross-organisation comparison of qualitative interview findings: actionability and organisational explanation

Organisation	Actionability	Organisational embedding	Ownership/responsibility	Main barrier or contextual condition	Main interpretation
Interviewed organisation 1	Medium–high; information can trigger strategic investment discussions, but follow-up may be delayed.	Partly embedded in monthly reporting, but weaker in operational routines.	Mainly high-level; local responsibility is not yet sufficiently embedded.	Dashboard use sits too high in the organisation; operational follow-up routines remain underdeveloped.	Strong strategic dashboard value, but performance improvement depends on clearer local ownership and routine follow-up.
Interviewed organisation 2	Medium; supports pilots and internal conversations, but direct causal steering remains difficult.	Embedded in reporting and selected projects, but less in daily operations.	Sustainability acts as connector between finance, supply chain, operations, and suppliers.	Fragmented responsibilities and indirect control over waste generation.	Dashboard functions as a coordination tool in a complex organisation rather than as a direct operational steering tool.
Interviewed organisation 3	Medium; action often arises through Milgro's interpretation rather than direct internal dashboard analysis.	Used in reporting peaks, especially during annual reporting periods, but not structurally embedded in operations.	ESG monitors; operations and plant teams must act.	Partial platform coverage, changing responsibilities, tool fatigue, and plant-level data outside Milgro.	Value lies in standardised reporting and external accountability; operational action is often mediated by Milgro.
Interviewed organisation 4	High; deviations lead to actions, action registers, and follow-up in monthly routines.	Embedded in monthly KPIs and plant team meetings.	Monitoring is centralised, while action lies with departments and team leaders.	Time and limited dedicated capacity.	Strong case where dashboard information is translated into routines, action ownership, and follow-up.
Interviewed organisation 5	High; supports actions around wood containers, pallet reuse, transport reduction, and classification issues.	Embedded in operational processes, monthly reports, site meetings, and customer meetings.	Facility reports; operations, site management, and contract management act.	Delayed data and missing information on transport numbers and container filling levels.	Dashboard supports both reporting and logistics optimisation when linked to customer demands and operational routines.
Interviewed organisation 6	Low–medium; mainly produces insight and meta-discussions about data quality and missing streams.	Embedded in reporting cycles, less in operational steering.	Fragmented across sustainability, facility services, circularity programmes, departments, and care processes.	Healthcare complexity, missing streams, definitions, protocols, scale, and many actors.	High dashboard use remains mainly informational because action is organisationally and operationally complex.
Interviewed organisation 7	Low; dashboard information is not used locally.	Lightly embedded in local administrative routines.	Local administration uses the platform; dashboard monitoring is handled centrally.	Dashboard is not locally relevant; standard waste is mostly automatically collected.	Local platform use is operational, while analytical dashboard engagement sits centrally.
Interviewed organisation 8	Medium; central insight can trigger questions and awareness, but local action remains difficult.	Strong at central service level, weak at local member level.	Central monitoring; local entrepreneurs must act.	Cooperative structure, dashboard literacy, space constraints, and local autonomy.	High central engagement does not automatically translate into local circular-performance improvement.
Interviewed organisation 9	Medium; can feed conversations, but many insights do not lead to direct action.	Embedded in reporting and Milgro meetings, weak in internal improvement routines.	Responsibility split between sustainability and facility/internal service.	Limited scale, capacity, practical constraints, and low urgency.	Dashboard quality is not the problem; limited organisational priority and practical feasibility constrain action.
Interviewed organisation 10	High outside the dashboard; deviations lead to internal action through QA/QC and plant management.	Strong internal routines outside Milgro.	Operations, QA/QC, and plant management share responsibility.	Platform is too slow for short-cycle food-production dynamics.	Low Milgro-dashboard engagement can coexist with high performance when waste monitoring and follow-up are supported by alternative internal information platforms and embedded routines outside the Milgro dashboard environment.
Interviewed organisation 11	Low; action mainly arises after Milgro's annual presentation or external questions.	Weak; mainly annual reflection moment with Milgro.	Overarching role exists, but action must take place in separate business units.	Low priority, limited time, and limited capacity.	Platform use remains reactive and report-oriented, with weak internal routines for continuous improvement.
Interviewed organisation 12	Low; dashboard information is too general and not linked enough to responsibilities.	Weak; mostly reactive and issue-driven.	Facility partly owns waste management, but dashboard follow-up is unclear.	Logistics priority, limited ownership, weak integration, and platform perceived as extra administrative layer.	Conditions for sustained platform engagement are not yet in place.
Interviewed organisation 13	Medium–high; actions arise mainly through quarterly/yearly review and Milgro discussions.	Embedded monthly, quarterly, and annually.	HSEQ manager owns monitoring; logistics handles operational orders.	Delayed data and need for process knowledge.	Strong monitoring case, but dashboard actionability mainly develops over longer time horizons.

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Organisation	Actionability	Organisational embedding	Ownership/responsibility	Main barrier or contextual condition	Main interpretation
Interviewed organisation 14	Low; no dashboard-driven action.	Embedded only as a practical operational task.	Local facility role uses platform; higher-level ownership is unclear.	Limited access, incomplete overview, support issues, and perceived extra intermediary layer.	Platform use is practical but not strategic; dashboard value is invisible at local level.
Interviewed organisation 15	Low; not a leading source for improvement actions.	Embedded in reporting only.	QHSE/facility uses data; improvement is not dashboard-driven.	Low perceived need, stable flows, limited volumes, and supplier dependency.	Dashboard is useful but not necessary for improvement in a relatively stable waste context.
Interviewed organisation 16	Medium; action occurs when deviations are noticed.	Operational ordering is embedded; dashboard analysis is ad hoc.	Order placement is distributed; monitoring partly central.	Missing alerts, access issues, limited priority, and distributed operational responsibility.	Action occurs when problems are noticed, not through systematic dashboard steering.

J | AI Statement

This thesis was written within the course EPA2942 Master Thesis of the Faculty of Technology, Policy and Management at Delft University of Technology.

In writing this thesis, I:

- used generative AI to generate ideas and obtain inspiration;
- used generative AI to structure the text, for example by asking for suggestions regarding sections, paragraphs and transitions;
- used generative AI to improve the grammar, style and spelling of the text.

More broadly, generative AI tools were used strictly as supportive instruments during the writing process and not to generate this thesis in its entirety. The following AI tools were used:

- ChatGPT (OpenAI): used for brainstorming, structural refinement, clarification of methodological terminology, and language improvement. AI suggestions helped to create more logical transitions between the different questions that had to be answered. After conducting my own checks, AI was used as an additional safeguard to ensure that terminology and formatting were applied consistently across the different sections of this thesis.
- Gemini Pro (Google): used for alternative phrasing suggestions and reflection on structural coherence. Drafted paragraphs were reviewed using AI to improve grammar, sentence clarity and professional tone. All revisions were checked manually, and final decisions were made based on my own judgment.
- Perplexity AI: used as a search-support tool to identify potentially relevant academic sources and policy documents. Sources identified through this tool were not used automatically, but were checked manually before being included in the thesis.

Verification and safeguarding academic integrity

All AI-generated output was carefully reviewed, edited and validated before inclusion. In particular:

- No AI-generated references were used without manual verification. All references included in the thesis were checked for authenticity through Google Scholar or the original publisher.
- Academic claims were only included when supported by peer-reviewed literature, policy documents, empirical data or the author's own analysis.
- AI was not used to independently generate the analysis, findings, arguments or conclusions of this thesis. These elements are the result of my own interpretation, synthesis and critical reflection.
- AI-generated suggestions were treated as draft suggestions only. They were accepted, rejected or adapted based on my own academic judgment.
- The empirical analysis, coding decisions, interpretation of interview data and integration of quantitative and qualitative findings were conducted and checked by the author.

This thesis is the result of my own synthesis of academic literature, empirical material and analytical reasoning. AI was only used as a support tool, in full compliance with the academic integrity policies of TU Delft.

Prompts used

To provide transparency, examples of prompts used during the writing process are listed below. These prompts are representative of the types of AI support used and were always followed by manual review, revision and verification.

- "Can you help me improve the structure of this section so that the argument flows more logically from the research question to the methodological choices?"

- “Can you rewrite this paragraph in more academic English while preserving the meaning, terminology and argumentation?”
- “Can you check whether this paragraph clearly explains the difference between platform engagement, dashboard use and circular-performance outcomes?”
- “Can you suggest a clearer transition between the quantitative results chapter and the qualitative case-selection chapter?”
- “Can you identify whether there are repetitions between these two sections and suggest how they can be merged into one coherent paragraph?”
- “Can you improve the grammar, sentence structure and academic tone of this text without changing the content?”
- “Can you suggest possible academic search terms for literature on digital platforms, circular economy dashboards and organisational engagement?”
- “Can you check whether the terminology in this section is used consistently, especially terms such as dashboard engagement, platform use, circular performance and organisational follow-up?”