Elum Designs:

Predictive Analytics Implementation Proposal

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Nikolas Barrett and Team

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<u>Company Contact Information</u>

Name: Elum Designs

Main contact: CEO Bradley Foster

Email/Number: brad@elumdesigns.com / (858) 650-3586

Executive Summary

Elum Designs is a San Diego-based design and manufacturing company specializing in seasonal consumer goods, including greeting cards, wrapping paper, candles, and art pieces. Major retail partners include TJ Maxx, Ross, HomeGoods, Macy's, and Nordstrom. Elum Designs creates value by delivering on-trend seasonal assortments to these retailers, but fragmented tools and disconnected data constrain operations. Creative, production, compliance, and logistics teams each maintain separate spreadsheets and applications (Google Sheets, Microsoft Excel, TeamGantt, MediaValet, and email), which do not share a common view of designs, buyer feedback, and sales results. In a seasonal business, these gaps create inefficiencies, miscommunication, and a higher risk of missed floorsets, which can mean losing most of the revenue for an entire holiday cycle.

To address these enterprise-level problems, this project recommends a cloud-based predictive analytics system built on Google Cloud Vision API and Qualtrics CoreXM, with a simple cloud data warehouse such as Google BigQuery serving as the integration layer. Google Cloud Vision will automatically tag every new artwork file with consistent visual metadata (palette, motif, style, text). At the same time, Qualtrics CoreXM will capture structured buyer and consumer feedback for key concepts. These features will feed a predictive model that scores each design on its likelihood of selection and reorder, allowing Elum Designs to prioritize high-value concepts earlier in the process and reduce trial-and-error design cycles.

Based on conservative estimates developed during this project, the proposed system is expected to increase design selection rates by approximately 25%, reduce average design-cycle time by roughly 30%, and cut wasted creative labor by about 40% over the next 12–18 months. Financially, the combined cost of Qualtrics licensing, Google Cloud usage, and light integration work is estimated at approximately $45,000 over three years, while the reduction in wasted designer hours, rush fees, and missed seasonal opportunities is expected to generate about $135,000 in quantifiable benefits over the same period. This yields an estimated ROI of roughly 200% and a payback period of about 12 months. Key performance indicators for this initiative include design selection rate, time from concept to buyer approval, and the proportion of designs that never enter production. If implemented, the proposed system will move Elum Designs from intuition-driven seasonal decisions to a repeatable, data-supported process that better leverages its creative strengths and long-standing retail relationships.

Business Analysis

Enterprise Analysis

Elum Designs operates as a mid-sized design and manufacturing company, specializing in the seasonal consumer goods industry. Founded in 2001, the company sells design-driven stationery, gifts, and lifestyle products to national retailers, including off-price chains and specialty stores, generating multi-million dollar annual revenue. In the company, there are around 20-30 employees, selling to retail companies such as TJ Maxx, Ross, and HomeGoods. The enterprise creates value by consistently delivering fresh, on-trend artwork that retailers can turn quickly on their shelves. Revenue and margin depend on placing the right SKUs into each seasonal assortment, hitting tight delivery windows, and minimizing write-offs on slow-moving or late products. Elum Designs succeeds when its creative output aligns closely with retailer demand, when production and logistics stay on schedule, and when the same creative effort generates multiple successful SKUs instead of one-off misses.

Elum Designs aims to improve efficiency, modernize operations with predictive analytics, and align design output more tightly with buyer demand. At the enterprise level, these goals translate into specific strategic performance measures. Current internal estimates indicate that less than half of all designed artwork proceeds to production, meaning that a significant portion of designer time does not generate revenue. Design cycles can extend well into a season, increasing the risk of missed retailer floorsets or compressed margins. The enterprise has set target metrics to increase design selection rates by approximately 15 percentage points, reduce average design-cycle time by about 20%, and decrease creative labor waste by approximately 30%.

Design Selection Rate is defined as the percentage of unique seasonal design concepts that are selected by at least one retail buyer and subsequently move into production. For example, if 25 out of 50 seasonal concepts are approved by production in a given line, the design selection rate would be 50%.

Average Design-Cycle Time is measured as the number of calendar weeks from initial concept briefing to final buyer approval for a seasonal line. In practice, the difference in calendar weeks between the initial brief date and final buyer approval date for each line would be taken, then averaged across the season.

Creative Labor on unproduced concepts is estimated as the share of total designer hours spent on artwork that never progresses to production. The percentage would be estimated by comparing the designer's time spent on concepts that never received buyer approval to total design hours in a season.

Summarized Plan:

Enterprise KPI	**(Estimated) Baseline**	**Target Estimate Goal (12-18 months)**
Design Selection Rate	45% of Designs Produced	60% of Designs Produced
Average Design-Cycle Time	16 weeks per season	12 weeks per season
Creative Labor	40% of Designing Hours	28% of Designing Hours

The enterprise SWOT analysis reinforces these priorities. Strengths include exceptional creative talent, the ability to produce large volumes of high-quality artwork quickly, and long-standing relationships with national retailers that trust Elum Designs to fill seasonal assortments. Weaknesses center on reliance on manual, unintegrated systems such as spreadsheets, email threads, and separate applications, which limit data sharing, obscure the link between artwork, buyer decisions, and sell-through, and make it difficult to reuse past learning in future seasons. Opportunities include adopting predictive analytics and artificial intelligence to forecast buyer behavior, rank new concepts before buyer meetings, and optimize which designs move into product development. Threats include fluctuating retail demand, overseas manufacturing and logistics risk, and increasing competition from brands that are already applying artificial intelligence to narrow their assortments and shorten their calendars.

Business Area: Problems, Opportunities, and Directives

The Creative and Product Design business area sits at the center of Elum Designs' enterprise performance. This group produces seasonal collections that account for the majority of annual revenue. Critical success factors for this business area include (1) on-time seasonal delivery to key retailers, (2) high design selection rates in buyer line reviews, and (3) innovation that matches consumer trends without overloading designers with low-value work. The current creative process in place depends heavily on intuition, manual documentation, and non-integrated tools. This lack of integrated analytics and processes prevents the company from generating a consistent identification guideline for which design elements, such as patterns, motifs, formats, or palette, are most strongly correlated with retailer selection and reorder retention. The result is repeated similar design cycles, limited design time allocated to revenue-driving designs, and overproduction of unsuccessful concepts. Three main KPI were put in place for the Creative and Product Design business area:

Design selection efficiency measures the ratio of seasonal designs created to those actually selected by buyers. For instance, if the design team created 25 designs and buyers selected 15, the design selection efficiency would be at a 60% hit rate.

Redundant design cycles represent the percentage of designer time spent on concepts that are never shown or never selected. This would be estimated by tracking concepts that are either never presented or not selected, then calculating the share of design hours put to developing those concepts compared to the total design concept hours in a given season.

Full design cycle duration measures the elapsed time from the first design sketch to a buyer-ready assortment across key retail partners. The initial date a design appears on the seasonal schedule to the date it is ready for a buyer presentation would be calculated and averaged across a given season.

- Refer to ***Exhibit A***

Business Area KPI	**(Estimated) Baseline**	**Target Estimate Goal (12-18 months)**
Design Selection Efficiency	30-50 designs produced per season, roughly 50% selected by buyers	20-30 designs produced per season, roughly 70% selected by buyers
Redundant Design Cycles	30-40% of designing time spent on concepts that are never showcased/selected	<20% of designing time spent on concepts that are never showcased/selected
Full Design Cycle Duration	16 weeks from design conception to buyer-ready	12 weeks from design conception to buyer-ready

All the values are estimates based on feedback received during numerous meetings and interviews, and represent the general targeted direction the proposed solution aims to derive. The present problems can be broadly divided into 3 main points and further understood through the use of root cause analysis.

- Refer to ***Exhibit B***

Point 1: Design Cycles are long, inefficient, and more unsuccessful than not. With the creative process being driven largely by trial and error and manual iteration, design cycles can extend longer than necessary. Designers often create multiple variations of similar concepts and revise them repeatedly based on subjective feedback, which slows the path from concept to buyer-ready line. Designers lack early-stage, data-driven indicators of which ideas are likely to succeed, so they iterate broadly rather than strategically. Buyer and consumer signals arrive late in the process, which means the team invests time in low-probability concepts before they realize those concepts are unlikely to be selected. These long cycles increase the risk that assortments are finalized late, which can jeopardize on-time delivery for seasonal floorsets and reduce Elum Designs' ability to negotiate optimal orders. The opportunity presented in this issue is early scoring/ratings of designs based on art attributes. Structured feedback can help the business area reduce the number of unused design iterations and shorten the design conception to the buyer's timeline to meet the 12-week target estimate goal, while enhancing creative quality.

Point 2: The design selection process is inefficient, ineffective, and underperforming, creating inconsistencies with information. The Creative and Product design team relies heavily on intuition and manual documentation to decide what design concepts move forward. Designers typically produce 30-50 designs per season, and only about half of the bunch are selected. A substantial portion of creative labor is wasted and does not contribute to revenue-generating SKUs. Buyer and consumer feedback is captured in email threads, informal notes, and unstructured Google Sheets. There is no integrated analytics capability to link specific design attributes (palette, motif, style, format) to buyer selection decisions or sell-through. Without clear evidence of what has worked historically, Designers and Account Managers must rely on instinct and past anecdotes, leading to overproduction of exploratory designs and repeated design cycles. The opportunity presented in this issue is to introduce a predictive analysis system that can quantify and index design attributes and indicators that have historically been associated with driving buyer selection, giving the creative team the ability to center their focus on designs with a higher probability of being selected by buyers, with the target estimate goal being increased design selection efficiency from roughly 50% to near 70%.

Point 3: The feedback loop between the buyer and creative is inconsistent and not readily accessible. There is no current reliable and structured feedback loop in place to help creatives understand buyer trends and thoughts. The available buyer feedback is generally unstructured and undetailed text, while being dispersed across various spreadsheets, emails, and personal notes. This then leads to an absence of a standard system for capturing design attribute feedback, resulting in the Creative and Product design team having no system in place that identifies combinations and trends of attributes that perform best by season, retailer, or price. The opportunity presented in this case is the implementation of a structured feedback loop and analytics layer that can convert buyer responses to numeric scores and tagged indicators, and themes. A closed feedback loop model would be employed, enabling the use of historical data and trends to analyze a design concept, resulting in an estimated success value that can help improve information quality and indicators, before concepts are decided to move on to physical samples and presentations. In enlisting a closed feedback loop rather than an open loop, buyers' reactions and sales outcomes are captured in a structured manner, fed back into the analytics layer, and used to influence which designs are prioritized in future seasons. Each season's results effectively become training data for the next season's decisions.

Directives for the Creative and Product Design business areas set the framework for the systems that are viable for implementation in this area. The enterprise had a key behest on modernizing decision-making capabilities through the use of predictive analytics and the ever-growing and present artificial intelligence industry, but the essence of the enterprise's identity was built on creativity and subjectivity; therefore, a completely algorithmic approach and process to design analysis was not part of the scope. In a similar vein, while reducing the amount of wasted time and labor spent on unsuccessful concepts was a focal point in the solution, the aspect of uniqueness and innovation did not want to be completely stripped from designers due to the numbers, but rather reworked into higher probability concepts. Lastly, the direction of implementing new systems in place was all about integration and working to leverage the preexisting systems present in the business area, such as NetSuite and MediaValet. The additions were meant not to disrupt or negatively suboptimize existing systems and workflows but instead synergize with them, leading to greater alignment and optimization.

Current System Analysis: Process Overview

Physical Narrative

- Refer to ***Exhibit C***

Elum Design's current workflow follows a traditional seasonal creative cycle. The process begins when the Product Development Manager and outside trend providers research seasonal trends and quarterly timelines. Using this information, the Product Development Manager creates a design schedule and workflow that defines timelines, due dates, and design strategies for the upcoming season. The manager shares these details with the design team through Team Gantt to guide creative direction.

Designers then produce new seasonal artwork, developing and reviewing 30–50 different designs. After approving specific pieces, designers manually assign attributes to each one and store the files in Media Valet for digital management. The designers then send the approved artwork files to the product development team, who create prototypes and mock-ups for specific product types. They also determine product specifications, packaging, and potential pricing, and add these details to the product designs. The team then builds presentations for buyer review and stores them in Media Valet.

Once the product designs are ready, the sales team prepares formal buyer presentations that showcase seasonal designs and proposed concepts. They categorize the designs, create buyer-specific presentations, and store these files in their Google Drive. Elum Designs then presents the concepts to buyers, who review the designs and select preferred options for production.

During these meetings, the sales representative records buyer feedback manually and delivers the notes to the designers. The designers then update the buyer presentations and return them for approval. Once buyers approve the revised designs, the team finalizes the product prototypes and artwork to prepare for production. Finally, the Production Department receives the approved designs and uploads them to Media Valet and Excel sheets.

Summary of Problems and Performance Targets

Elum Design's workflow currently involves several unconnected applications and a long design process. The creative team uses MediaValet to store and catalog digital artwork. The project management process is tracked through TeamGantt, which manages seasonal product development timelines and critical deadlines. Sales staff track buyer selections and SKU information in Excel or Google Sheets. The production team communicates final specifications through email or shared drives. Because these systems are siloed, data transfer between processes is slow and prone to error. The lack of integration makes it difficult for management to gain a clear view of project status, production readiness, and overall workflow efficiency. The fragmented infrastructure contributes to duplicated efforts and limited visibility across the organization. Missed deadlines, long processes, and miscommunication during key seasonal periods, such as Q4, impact Elum Design's ability to deliver its products on time to major retail partners. This results in a huge potential loss in sales and revenue opportunities.

The primary challenges include a lack of integrated data, manual reporting, and minimal forecasting capabilities. Baseline performance shows that designers produce 30–50 concepts per season, with only about 50% ultimately selected, 30–40% of design time is spent on unselected or unused concepts, and the full design cycle averages 16 weeks from conception to buyer-ready. The target improvements aim to increase buyer selection to roughly 70% across a leaner set of 20–30 designs, reduce redundant design work to below 20%, and shorten the overall cycle to 12 weeks. The target performance improvements are a 25% percent increase in design selection, a 30% reduction in the design-to-approval timeframe, and a 40% decrease in unproductive creative work. Elum will be able to meet these objectives using predictive analytics and by guiding design priorities with data-driven insights.

Proposed System Analysis

Proposed Technical Solution

- Refer to ***Exhibit D and E***

The proposed system will use a cloud-native predictive analytics stack comprising three main components: Google Cloud Vision API, Qualtrics CoreXM, and Google BigQuery, a cloud data warehouse. All three elements are delivered as Software-as-a-Service (SaaS) or Platform-as-a-Service (PaaS), so the solution will not require any on-premise servers or local application installs. End users and internal applications will access the system through standard web browsers or RESTful API calls over secure HTTPS connections.

Google Cloud Vision API is a managed computer-vision service that runs on Google Cloud Platform. It exposes a set of REST endpoints that accept image files such as JPG and PNG and return structured JavaScript Object Notation (JSON) responses. Calls to Vision are authenticated using Google service accounts and OAuth 2.0, and the traffic is routed through Google's global backbone network. The underlying infrastructure, GPU/CPU clusters, operating systems, storage, and autoscaling, is fully managed by Google. From a technical perspective, the Vision API behaves like any other web service; client systems send HTTP requests to a specific endpoint, include an API key or service account token, and handle the JSON response inside their own application logic or data pipelines.

Qualtrics CoreXM is a multi-tenant web application that provides survey design, distribution, and reporting as a cloud service. Users interact with CoreXM through a browser-based UI that runs on load-balanced application servers in Qualtrics' data centers. Response data is stored in managed relational databases and can be accessed through built-in export tools (CSV, JSON) or through APIs that support system-to-system integration. Authentication is handled through username/password, Single Sign-On (SSO), or Security Assertion Markup Language (SAML), and access is controlled with role-based permissions. CoreXM also provides native connectors to common BI platforms and cloud data warehouses, which allows survey and feedback data to be pushed into an external analytics environment without custom networking code. The baseline price for Qualtrics' surveys is $5,000 for 1,000 surveys. This would be an investment to gather initial data about consumer preferences, to understand what types of designs and products to focus on producing.

For centralized storage and analysis, the proposed solution will use Google BigQuery as a central cloud data warehouse and back-end data platform. BigQuery is a fully managed, columnar data warehouse service that supports ANSI SQL queries and separates storage from compute. Client systems will load data into BigQuery tables using batch imports, streaming inserts, or scheduled ETL jobs. Analytical users can query these tables directly through the BigQuery web console, through JDBC/ODBC connections from desktop tools, or through Connected Sheets, which allows a Google Sheet to function as a thin client on top of the warehouse. All communication with BigQuery occurs over HTTPS, and Google manages the underlying disk storage, file systems, operating systems, and query engine processes.

From a networking and platform perspective, the overall solution will follow a straightforward client–cloud architecture. Browsers and internal applications will act as clients; Google Cloud Vision, BigQuery, and Qualtrics will provide the server-side logic and storage. All components will communicate over encrypted HTTPS using commercial ISPs, with no requirement for VPN tunnels or custom network appliances. The vendors will be responsible for hardware provisioning, operating system patching, availability, and basic security hardening. At the same time, the client organization will be responsible for application configuration, managing API keys, and designing the data schema. With the implementation of these three key components, which make up the proposed system, their synergistic aspects will work effectively to create a technically sound, scalable, and maintainable predictive analysis model.

Application dashboards:

- Refer to ***Exhibits F and G***

  Exhibit F illustrates a sample configuration screen from the Google Cloud Platform (GCP) console for the proposed stack. The top portion of the figure displays the BigQuery web interface with a project, dataset, and table defined, and the associated schema fields. This illustrates where structured data, such as artwork tags, survey results, and sales metrics, will ultimately be stored and queried in the proposed solution. The lower portion of Exhibit F shows the "APIs & Services → Credentials" page, where an API key is created for the project. In the implemented system, Elum's IT support or implementation partner would follow a similar process to provision a cloud vision project, create the BigQuery datasets used by the predictive model, and generate secure credentials that allow internal tools such as Connected Sheets to access the data warehouse over HTTPS.

  Exhibit G presents the Qualtrics CoreXM "Create a project" screen. This view shows how a user selects the CoreXM category, chooses a Survey project, and then launches the guided setup for a new feedback or concept test study. In the proposed workflow, Account Managers will use this interface to create CoreXM survey projects that collect buyer or consumer reactions to seasonal designs. Once the survey is configured and launched from this screen, responses are captured in Qualtrics and then exported to BigQuery, where they are joined with the artwork metadata from Google Cloud Vision.

Artificial Intelligence Capabilities

The primary artificial intelligence capabilities of the proposed solution are automated feedback analysis, automated image tagging, and design selection scoring. Automated feedback analysis is delivered through Qualtrics CoreXM, which uses natural language processing (NLP) and machine learning models to process large volumes of survey responses, open-ended comments, and historical preference data. The platform converts raw text into structured data by detecting topics, extracting key phrases, assigning sentiment, and generating categorized numeric scores such as purchase intent or perceived fit. The vendor trains these language models on large corpora of survey and text data. They are continuously updated, so the client does not manage model training directly; instead, they configure which questions and comments feed into the AI analysis.

Google Cloud Vision API provides automated image tagging, exposing pre-trained deep learning computer vision models as a cloud service. When an image file is sent to the API, it returns a structured JSON response that includes detected labels, any readable text, and a set of technical features such as dominant color palettes, occasions, and iconography. Internally, Vision API relies on convolutional neural networks(CNNs) and related architectures that have been trained on massive, labeled image datasets. These models produce consistent metadata for every image, eliminating the need for the client to build or train its own vision models. In addition to these two capabilities, the proposed solution will support design selection scoring. In this layer, a supervised predictive model is trained on historical data that links image-level features from Google Cloud Vision and feedback-level features from Qualtrics to known outcomes such as "selected vs. not selected" or basic sell-through. The training process utilizes records as labeled examples, fits a model such as logistic regression, and validates it on a holdout set before deployment. Once trained, the model scores new designs by estimating their likelihood of being selected or reordered.

These AI and LLM capabilities differ fundamentally from traditional predictive analytical systems. Traditional systems typically operate only on pre-aggregated numeric fields such as units and price, stored in spreadsheets, and cannot synthesize the underlying artwork or read the original comments. In contrast, the proposed AI layer ingests unstructured data images and free-text feedback, uses deep learning and large language models to transform that data into rich feature vectors, and then applies supervised learning to generate forward-looking scores for new designs before any sales history is available. As a result, the system does not just report what worked last season, but instead provides a predictive signal that can influence design and selection decisions in future seasons.

Alternatives Considered

Various alternative technologies were evaluated before the proposed predictive analytics stack, comprising Google Cloud Vision and Qualtrics, was finalized. Two leading alternatives, Microsoft Power BI and Tableau, were analyzed as they are industry-standard platforms for business intelligence. Both applications are cloud-enabled BI tools that provide strong capabilities in data visualization, dashboarding, and analytic exploration. They can connect to relational databases, flat files, and cloud data warehouses, and support calculated fields, drill-down, and role-based security. However, the core strengths of Power BI and Tableau lie in descriptive and diagnostic analytics, rather than in end-to-end predictive modeling with unstructured data. They primarily answer the questions "what happened" and "why did it happen" by aggregating existing metrics. While both products can consume predictions generated by an external machine learning pipeline or host basic models through extensions, neither tool offers a first-class environment for training and deploying image-based or text-based AI models at scale. Relying on Power BI or Tableau alone would require a separate machine learning stack underneath them, which would increase the complexity of the overall solution.

Azure Computer Vision was also considered as an alternative to Google Cloud Vision, because it exposes similar computer-vision capabilities through REST APIs. Azure Computer Vision supports image classification, object detection, optical character recognition (OCR), and automated captioning, and it integrates tightly with other Azure services such as Azure Functions, Azure Storage, and Azure Machine Learning. It provides pre-trained models, supports custom vision scenarios, and returns structured JSON responses with labels and bounding boxes. However, adopting Azure Computer Vision would require maintaining a parallel AI stack in the Microsoft cloud while other data and collaboration services are centered around Google's ecosystem. That approach would introduce additional identity management, networking, and monitoring overhead for essentially equivalent computer-vision functionality. After carefully considering the trade-offs between the alternative technologies, the best balance of artificial intelligence capabilities, scalability, and seamless integration was found to be most substantial in the proposed predictive stack of Google Cloud Vision and Qualtrics CoreXM.

Proposed Physical Process Narrative

The new workflow will begin when designers upload new artwork to the integrated Google Cloud Vision API and Qualtrics platform. Upon upload, the artwork is automatically analyzed by the Google Cloud Vision API, which extracts image attributes such as color palette, object tags, and text content. The structured metadata generated from Vision API's JSON response is transmitted via secure RESTful calls and stored in Google BigQuery. This process enables predictive modeling: Qualtrics CoreXM will link this information with historical performance data, historical buyer feedback, and sales performance to calculate predictive success scores to estimate which designs are most likely to be selected by buyers. This process produces a predicted selected artwork dataset that informs the designers to prioritize designs with the highest probability of selection, as well as what attributes they should prioritize when creating new artwork for the future.

The predictive workflow continues as the selected artwork data in BigQuery becomes the foundation for downstream design and production processes. Once the predictive model identifies designs with the highest probability of buyer selection, these prioritized artworks are automatically shared with the creative and product development teams through MediaValet, ensuring that all stakeholders are referencing the same version-controlled files. Designers can use the predictive scores and metadata dashboards to make informed revisions or refine future collections, aligning creative direction with quantifiable buyer trends.

As these designs progress through the workflow, the Product Development team retrieves the corresponding artwork files from the Google Cloud Vision API and Qualtrics platform to generate product mockups, packaging templates, and prototypes. These mockups are re-uploaded to the new software and automatically linked to their artwork identifiers within BigQuery, maintaining data continuity between design and product. During the presentation phase, sales teams use PowerPoint decks created using the approved product designs that are enriched with analytics visualizations from the Google Cloud Vision API and the Qualtrics platform. Buyers receive presentations that include not only the visual concepts but also supporting data such as predicted popularity, color trend alignment, and seasonal performance metrics.

Buyer feedback is collected via Qualtrics CoreXM surveys, which are automatically parsed and stored in BigQuery. This feedback data feeds back into the predictive model, continuously improving the algorithm's accuracy by learning from actual buyer preferences and purchase decisions. Once final revisions are approved, finalized artwork files are archived in BigQuery and linked to production-ready specifications accessible to the Production Department. All communication across these stages, from Vision API processing to buyer analytics, is transmitted securely over HTTPS, with authentication handled through OAuth and SAML protocols. This integrated cloud ecosystem transforms Elum Designs' workflow from a fragmented, manual process into a streamlined, intelligent system that combines creativity with data-driven insights, ultimately reducing production delays, improving selection accuracy, and optimizing seasonal product success.

Solution Assessment

How the Solution Supports Elum Designs

The proposed system directly supports the enterprise by addressing its core operational challenges: siloed data, limited visibility into performance, and manual processes that slow down decision-making. By centralizing design, production, and sales information into a unified platform, the enterprise gains a single system for monitoring workflow efficiency, product profitability, and cross-departmental collaboration. This system aligns with the enterprise's need for scalability, improved communication between creative and production teams, and more accurate predictions for buyers and internal stakeholders.

Alignment with Strategic Goals

In the enterprise business needs section, the primary goals highlighted are increasing operational efficiency, reducing production delays, improving design success rates, and enhancing buyer satisfaction. The new system reinforces each of these goals through measurable outcomes and built-in performance indicators.

1. **Operational Efficiency**
   The system streamlines workflows by integrating design approval, product development steps, and vendor communication into one coordinated process. KPIs such as cycle time per design and turnaround time for revisions can now be automatically tracked. Because data is consolidated, managers can identify bottlenecks more quickly and adjust resources proactively. Implementing the predictive score and shared dashboards will move the full design-cycle duration from roughly 16 weeks to about 12 weeks and reduce the share of designer hours spent on concepts that never reach production from around 40% to approximately 20–28%.

2. **Improved Design Success Rates**
   With centralized sales and historical design performance data, the creative and product development teams gain insights into trends, best-selling themes, and buyer preferences. KPIs such as design acceptance rate and category-specific revenue contributions surfaced more clearly. Improvements in this key area allow the enterprise to make data-driven creative decisions, increasing the likelihood that new designs meet buyer expectations. This is expected to raise the Design Selection Rate at the enterprise level from roughly 45–50% to around 60% and increase Design Selection Efficiency within the business area from about 50% to roughly 70%.
3. **Scalability and Strategic Growth**
   As the enterprise expands, the system provides scalable reporting tools and automated analytics that support leadership in planning new product lines, identifying profitable designs, and forecasting demand. KPIs such as annual growth in product categories, profit margin by SKU, and market expansion metrics are supported through dashboard insights and trend analyses.

Proposed System Benefits

The proposed predictive analytics system delivers operational, strategic, and financial benefits across Elum Designs. Operationally, the integration of Google Cloud Vision and Qualtrics CoreXM reduces design-cycle time by automating metadata tagging, centralizing feedback, and creating insight into which designs are likely to succeed. This supports a more focused creative process that prioritizes high-probability concepts while reducing redundant design work. Strategically, the system shifts Elum from a reactive, intuition-driven model to a proactive, data-validated approach that improves alignment with buyer expectations. This enhances retailer satisfaction and positions the company as a more technologically advanced and reliable partner. Financial benefits include increased design selection rates, improved SKU performance, and better allocation of creative labor, all of which reduce wasted time and increase efficiency.

Proposed System Consequences

Despite its advantages, the system brings several short-term and long-term consequences that must be managed carefully. Employees may experience temporary process slowdowns as they adapt to new tools and analytical workflows. The introduction of AI-based scoring may challenge the traditional creative autonomy of designers, requiring clear communication to prevent resistance. There may also be an upfront time investment to clean existing data and build consistent standards for uploading artwork and recording buyer information. Additionally, the predictive model may initially produce imperfect insights until enough historical data is accumulated, which could lead to occasional misaligned prioritization of concepts. Long-term consequences include increased dependence on cloud vendors, potential subscription cost growth as usage scales, and the need for consistent data management to maintain model accuracy.

Stakeholder Impact

The primary stakeholders will be:

- **Creative Team**
  Designers will gain faster feedback and clearer direction on which concepts are most likely to resonate with retailers. This reduces wasted effort and allows them to focus on higher-impact creative work. However, designers may also feel pressure or creative constraint from data-driven scoring systems, making adaptive training and management essential.
- **Management and Executives**
  Leadership will gain improved visibility into design performance, season readiness, and workload distribution. Predictive insights support better strategic planning and resource allocation, and KPI dashboards will enable faster decision-making across product lines and seasonal cycles.
- **Retail Buyers**
  Although not involved internally, buyers receive more consistent, trend-aligned assortments that better meet their consumer profiles. This strengthens retailer confidence in Elum Designs and encourages repeat seasonal partnerships.
- **IT and Data Personnel**
  New responsibilities will include maintaining API connections, monitoring data quality, and supporting model updates. While the system is SaaS-based and reduces infrastructure needs, ongoing governance and oversight will still be required.

Short-term challenges may affect employees resistant to change, but comprehensive training and gradual rollout will minimize disruption and encourage adoption.

Feasibility and Risk Analysis

The proposed predictive analytics system is feasible for Elum Designs due to its cloud-based architecture, minimal hardware requirements, and scalable subscription-based pricing. However, several categories of risk must be carefully evaluated and mitigated to ensure successful adoption and long-term sustainability.

Technical Risks

System integration between Qualtrics CoreXM and Elum's existing tools, such as MediaValet, poses a high risk and should be mitigated with representation from a Qualtrics employee. Both Google Cloud Vision and Qualtrics CoreXM are reputable companies and have clients such as Meta, SAP, Microsoft, and Apple. The risk of incorrect API configuration, inconsistent data formats, or failed data flows may disrupt workflows or produce inaccurate insights. Continuous monitoring and retraining will be required as more validated research and examples accumulate.

Operational and Change-Management Risks

Employee adoption is a major variable in the system's success. Designers, sales staff, and operations teams may resist changes that automate parts of their workflow or reduce reliance on intuition. Training gaps could lead to misinterpretation of analytics outputs or incorrect data entry. Additionally, reorganization of data and design tracking may lead to lost files. To minimize these risks, a phased rollout, hands-on workshops, and a designated "systems manager" in each department should be put in place. Temporary dual operation of legacy systems may also be required to avoid workflow interruption.

Financial and Data-Quality Risks

Although subscription costs are predictable and relatively low (Refer to ***Exhibit A.1)***, financial risk stems from the possibility that survey data from Qualtrics fails to represent customer preferences or buyer behavior accurately. If the feedback sample is biased, incomplete, or underrepresentative of actual retail consumers, predictive outputs will not translate into profitable design decisions. Proper survey design and a diverse responder pool are essential to reducing this risk. Additional risk may arise from poor-quality historical design and sales data, which could impair model training. Elum must invest time in cleansing, standardizing, and validating all data before integration.

Security and Compliance Risks

As a cloud-based solution, the system introduces risks related to access control, misconfigured permissions, or weak security of sensitive data. Misuse or overexposure of artwork files and retailer insights could compromise both intellectual property and client trust. To mitigate this, Elum should implement Google Cloud IAM role-based permissions, centralized logging, and regular audits of data access. Qualtrics and Google Cloud already maintain strong security standards, but ongoing internal vigilance is necessary.

Overall, while risks exist, they can be effectively mitigated through structured planning, rigorous testing, ongoing training, and strong data management.

Implementation Plan

Elum Designs should begin the implementation process by consolidating and cleansing all existing design, product, and sales datasets to ensure the new system is built on accurate and reliable information. This initial data preparation stage is essential for reducing inconsistencies, eliminating duplicate records, and establishing categories that will later support stronger pattern recognition and analysis. Once the data foundation is in place, Elum can proceed with a structured pilot test of Google Cloud Vision using a limited collection of artwork files. Testing the system on a smaller, more controlled dataset allows the team to evaluate tagging accuracy, visual categorization performance, and the system's ability to surface meaningful insights about design themes or buyer preferences. Findings from the pilot will guide adjustments before the system is applied to the entire design archives.

After the pilot phase, Elum Designs should integrate Qualtrics CoreXM to incorporate buyer-feedback analytics into the workflow. This integration will allow the company to combine visual data from Cloud Vision with historical data, survey results, and qualitative insights from retail partners, providing a more complete understanding of which design elements resonate with customers. Once both systems are connected, a series of training sessions should be held to familiarize employees, particularly designers, product developers, and account managers, with the predictive tools, dashboards, and reporting features. These sessions will help ensure overall adoption and consistent use of the new capabilities in daily decision-making.

The final stage of implementation will focus on monitoring KPIs and refining model accuracy based on real-time results. Metrics such as design acceptance rates, sales percentages, category performance, and buyer satisfaction scores should be reviewed regularly to evaluate the effectiveness of the system. Continuous monitoring will enable the company to make iterative improvements, adjust data inputs, and refine the predictive models to better support long-term strategic planning. This ongoing optimization ensures that the system remains aligned with Elum Designs' operational goals and continues to deliver measurable value over time.

Conclusion

Overall, the proposed system offers Elum Designs a strategic solution to modernize its operations, improve design decision-making, and strengthen its competitive position in the retail market. By centralizing data, integrating predictive tools, and creating more transparency across departments, the system directly supports the organization's need for greater efficiency, accuracy, and creative alignment. The combined use of Google Cloud Vision and Qualtrics CoreXM ensures that both visual design patterns and buyer preferences are captured, analyzed, and transformed into actionable insights. This allows teams to create products that not only reflect artistic quality but also resonate more deeply with consumer preferences and market trends.

Beyond immediate process improvements, the system establishes a long-term foundation for scalable growth. As Elum Designs continues to expand its retailer partnerships and product categories, the analytical capabilities built into the platform will help leaders forecast demand, prioritize high-performing categories, and allocate resources more effectively. The ability to track KPIs, such as design acceptance rates, production accuracy, and buyer satisfaction, provides ongoing visibility into performance and supports smarter, more confident decision-making.

Ultimately, this solution strengthens the enterprise at every level: designers gain clarity about what sells, production teams experience fewer errors, account managers deliver better service to buyers, and leadership benefits from trustworthy data to guide strategy. By adopting this system, Elum Designs positions itself not only to optimize its current operations but also to innovate continuously and respond to evolving market needs with agility and insight.

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Exhibit A. Business Area Analysis

Business Area KPI	**(Estimated) Baseline**	**Target Estimate Goal (12-18 months)**
Design Selection Efficiency	30-50 designs produced per season, roughly 50% selected by buyers	20-30 designs produced per season, roughly 70% selected by buyers
Redundant Design Cycles	30-40% of designing time spent on concepts that are never showcased/selected	<20% of designing time spent on concepts that are never showcased/selected
Full Design Cycle Duration	16 weeks from design conception to buyer-ready	12 weeks from design conception to buyer-ready

Exhibit A.1.

Year	Implementation cost (one-time)	Ongoing cost - Qualtrics	Ongoing cost - Cloud & support	Total annual cost	Benefit - reduced design labor
1	$ 18,000	$ 5,000	$ 4,000	$ 27,000	$ 20,000
2	$ -	$ 5,000	$ 4,000	$ 9,000	$ 25,000
3	$ -	$ 5,000	$ 4,000	$ 9,000	$ 30,000

Benefit - reduced rush / rework fees	Benefit - avoided missed seasonal loss	Total annual benefits	Net cash flow (benefits - costs)	Cumulative net cash flow
$ 8,000	$ 7,000	$ 35,000	$ 8,000	$ 8,000
$ 10,000	$ 10,000	$ 45,000	$ 36,000	$ 44,000
$ 12,000	$ 13,000	$ 55,000	$ 46,000	$ 90,000

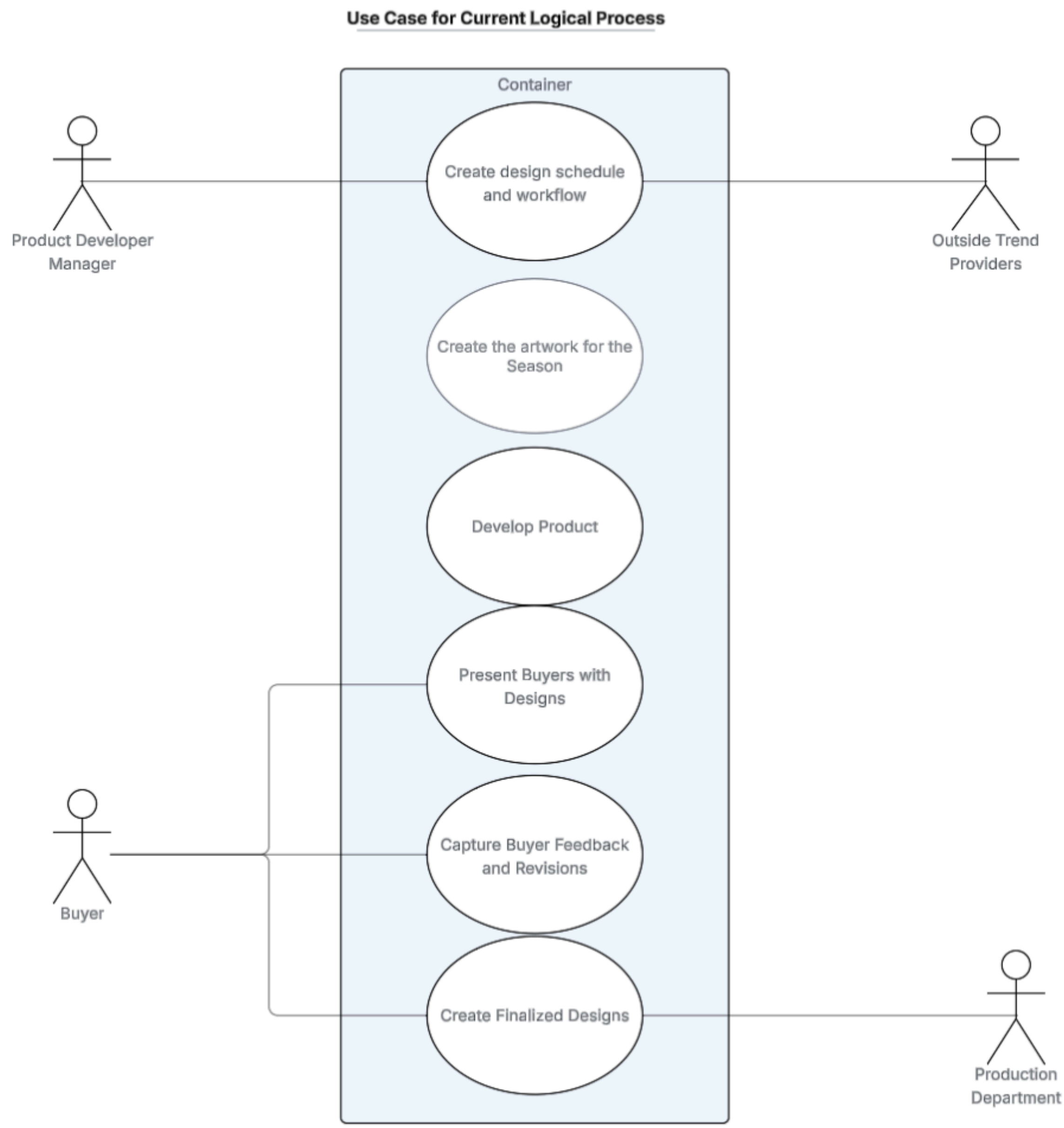
Exhibit B. PIECES Table (Process Analysis)

Category	**Issue/Opportunity**	**Description**
Performance	Long design process.	The design and product development teams take a couple of months to create artwork, and

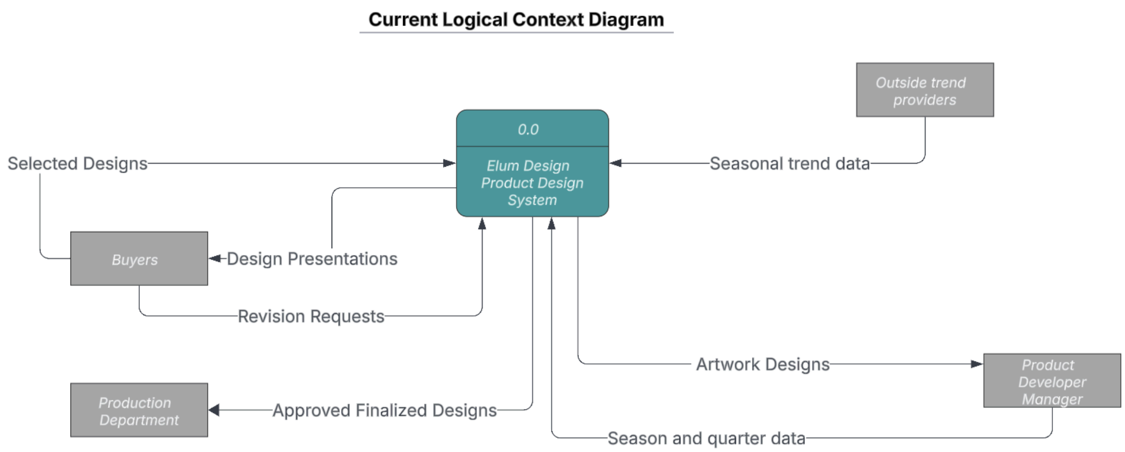
		50% are not selected, delaying the process and profit realization.
Information	Lack of integration.	Information such as creative assets is stored in silos with no synchronization among the systems (TeamGantt, spreadsheets, MediaValet)
Economics	Financial Inefficiencies	Costs the company money when many designs are not chosen and when there are delays with communication.
Control	Minimal control over data consistency.	Data is shared via email or between shared drives, creating miscommunication, long lead times, and inefficient processes.
Efficiency	Redundant communication	Data is shared via email or between shared drives, creating miscommunication, long lead times, and inefficient processes.
Service	Delayed Client Response	When inefficient processes lead to not meeting deadlines on time, it harms Elum Design's credibility and professionalism with its buyers.

Exhibit D. Current System Logical Data Flow Diagrams

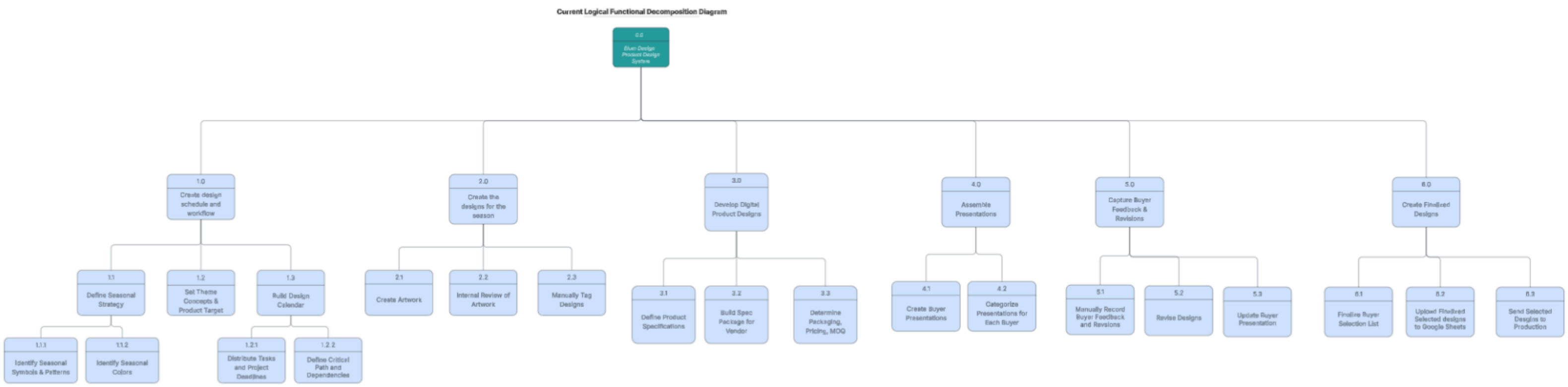
1. Current System Use Case Diagram



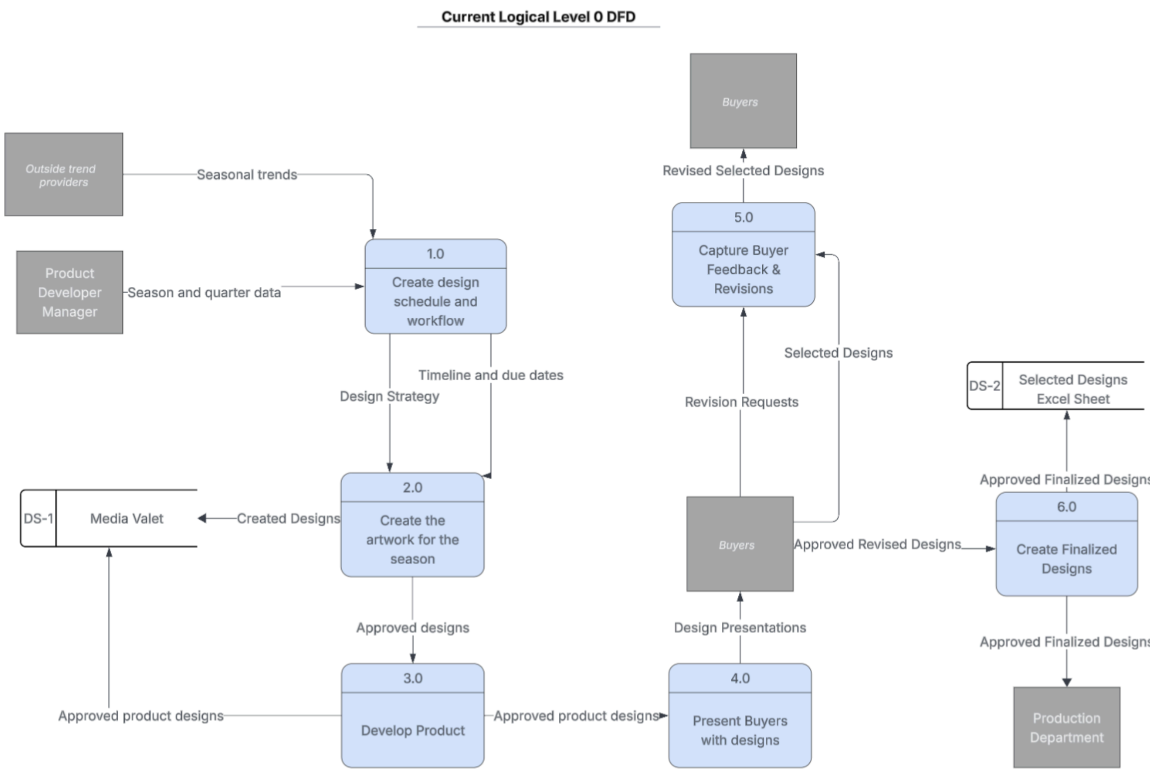
2. Current Logical Context DFD



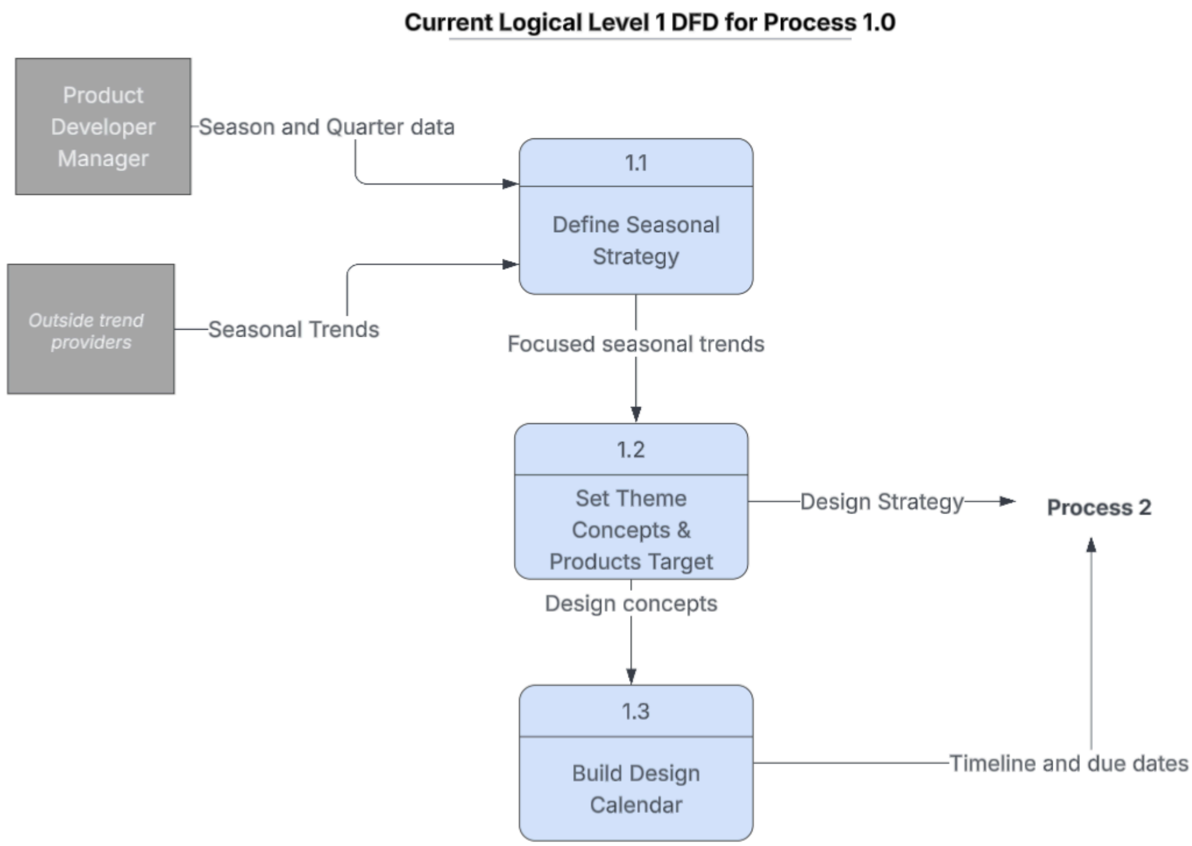
3. Current Logical Functional DFD



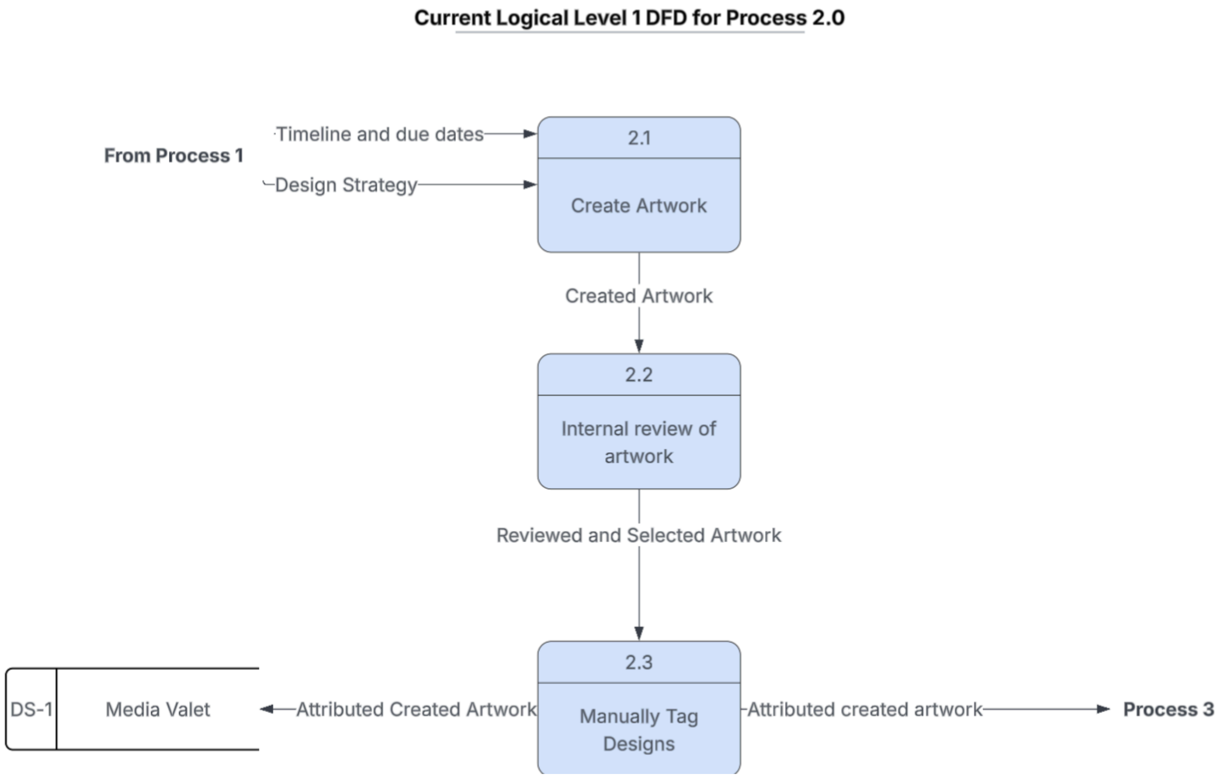
4. Current Logical Level 0 DFD



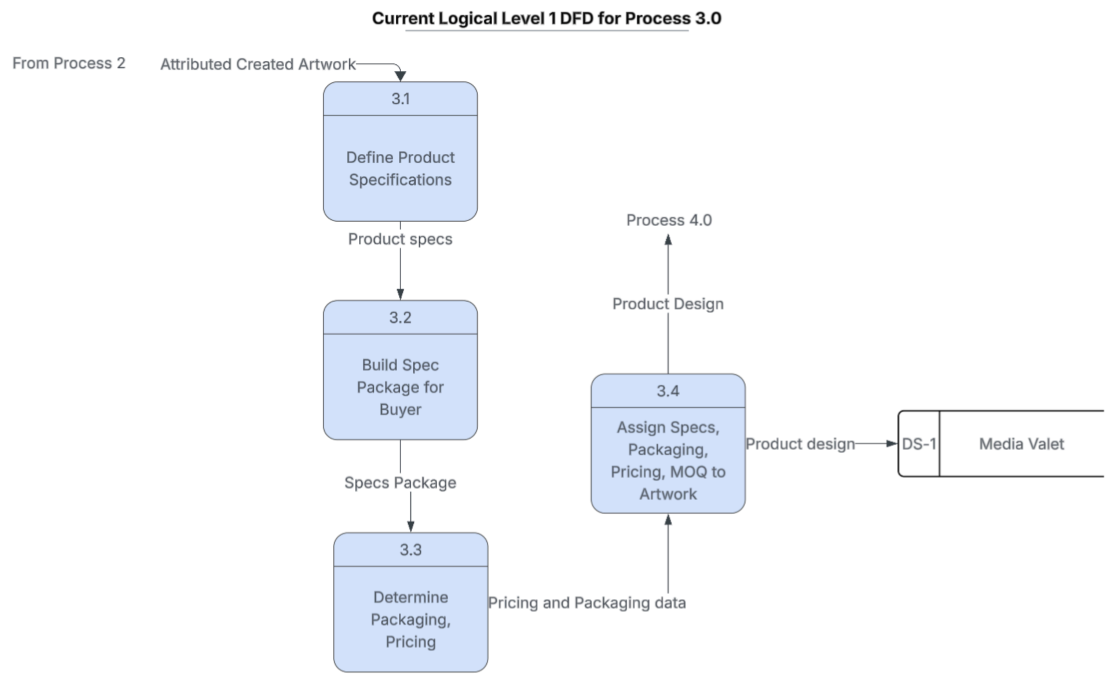
5. Current Logical Level 1 DFD for Process 1.0



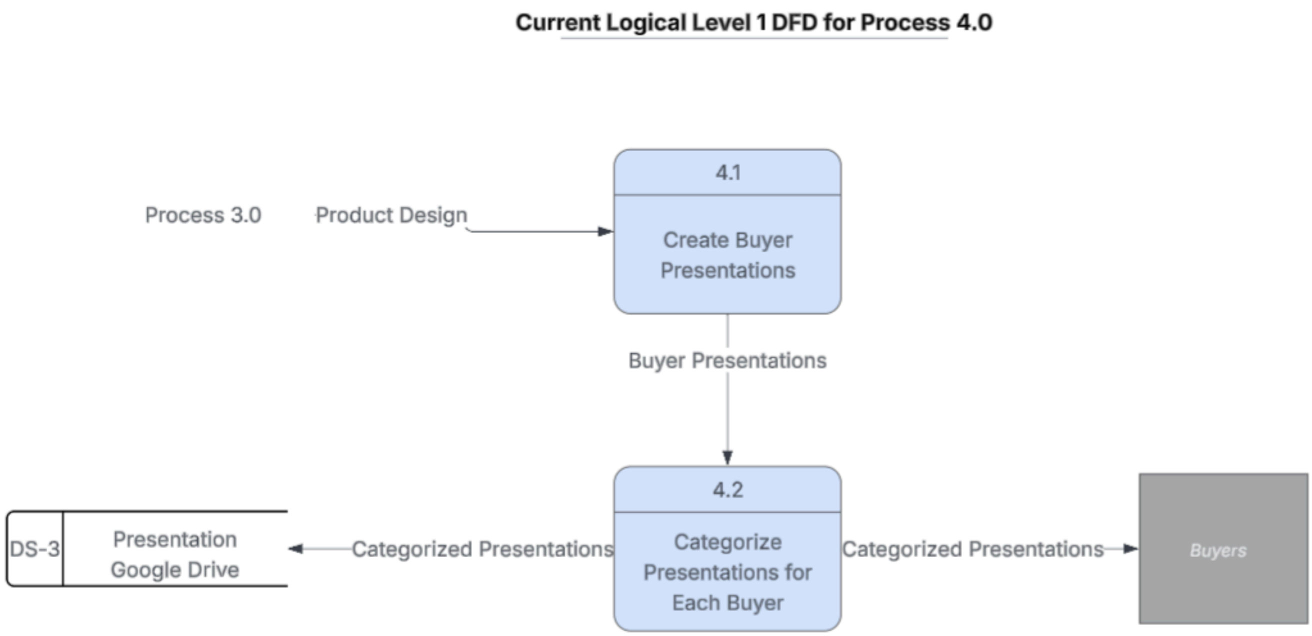
6. Current Logical Level 1 DFD for Process 2.0



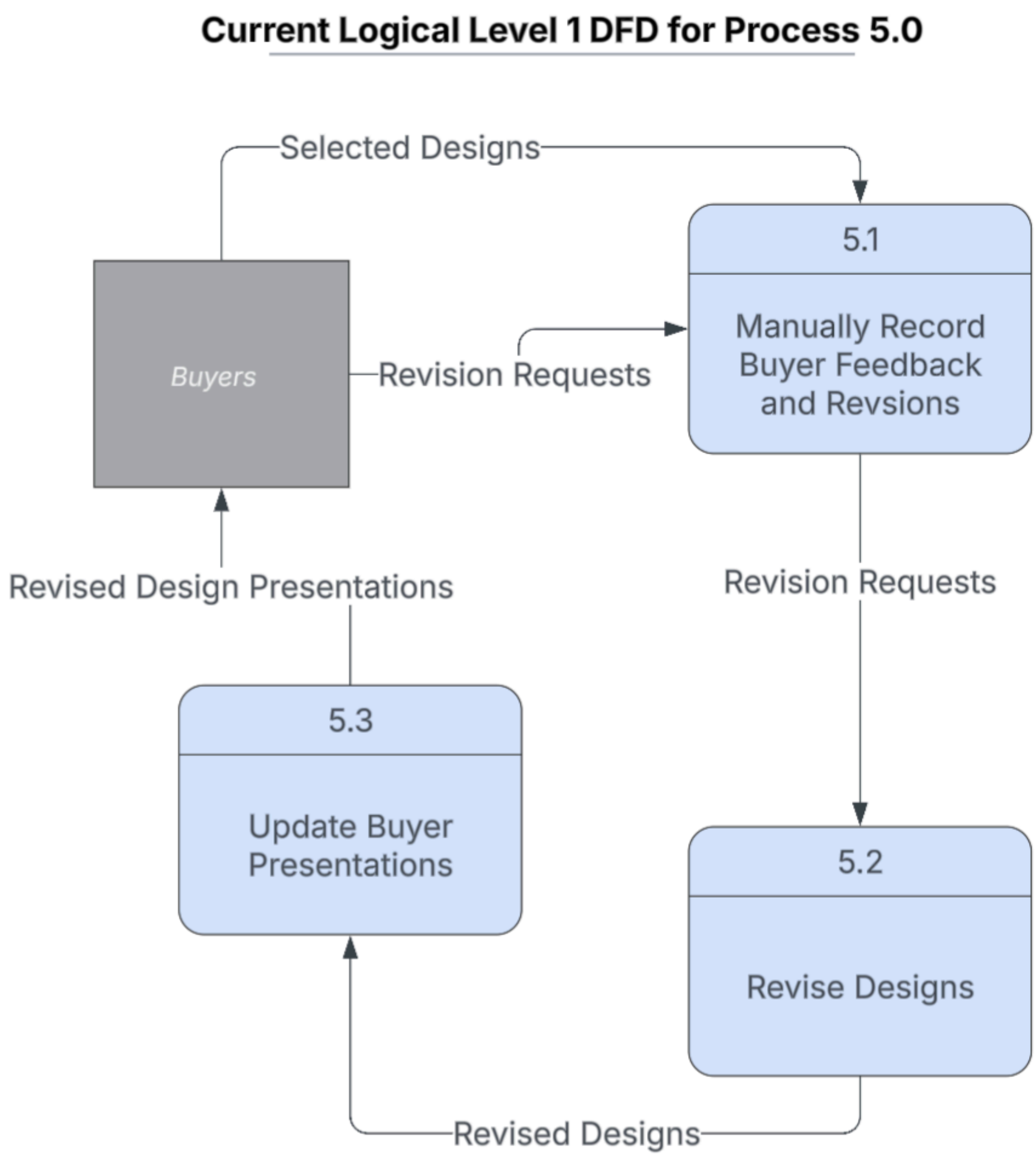
7. Current Logical Level 1 DFD for Process 3.0



8. Current Logical Level 1 DFD for Process 4.0



9. Current Logical Level 1 DFD For Process 5.0



10. Current Logical Level 1 DFD for Process 6.0

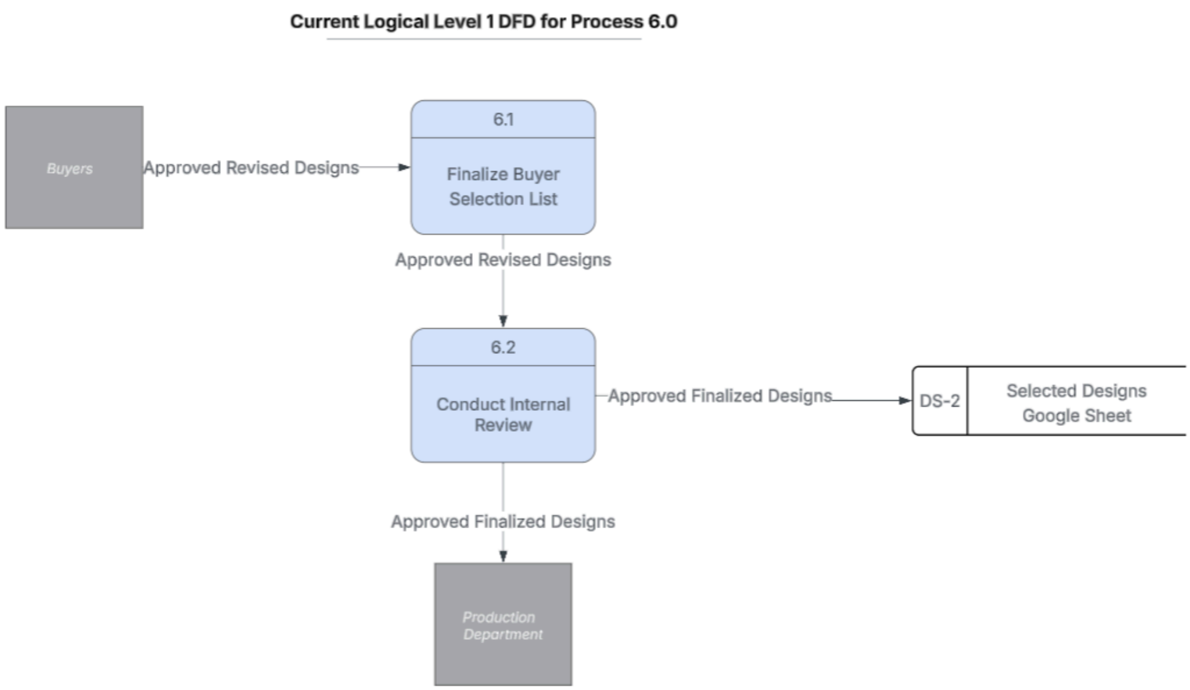
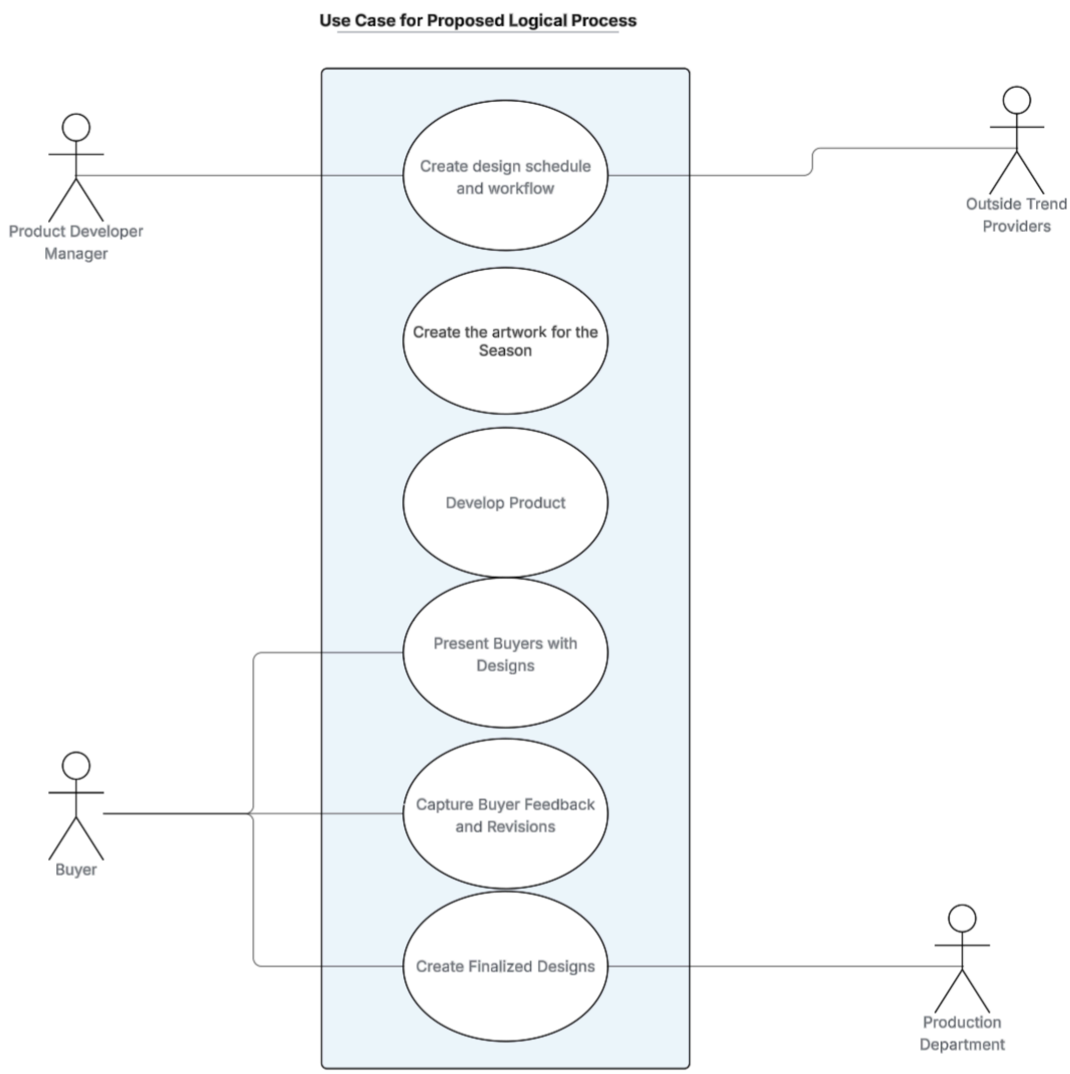
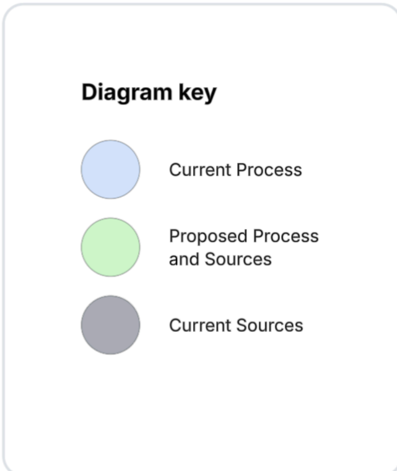


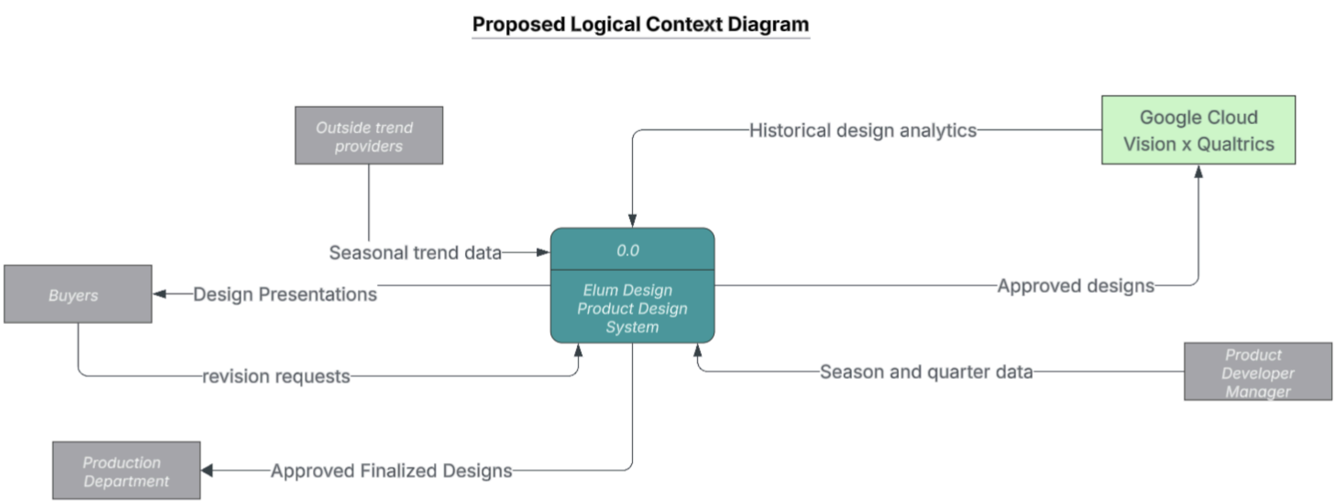
Exhibit D. Proposed Logical Data Flow Diagram

1. Proposed Use Case Diagram

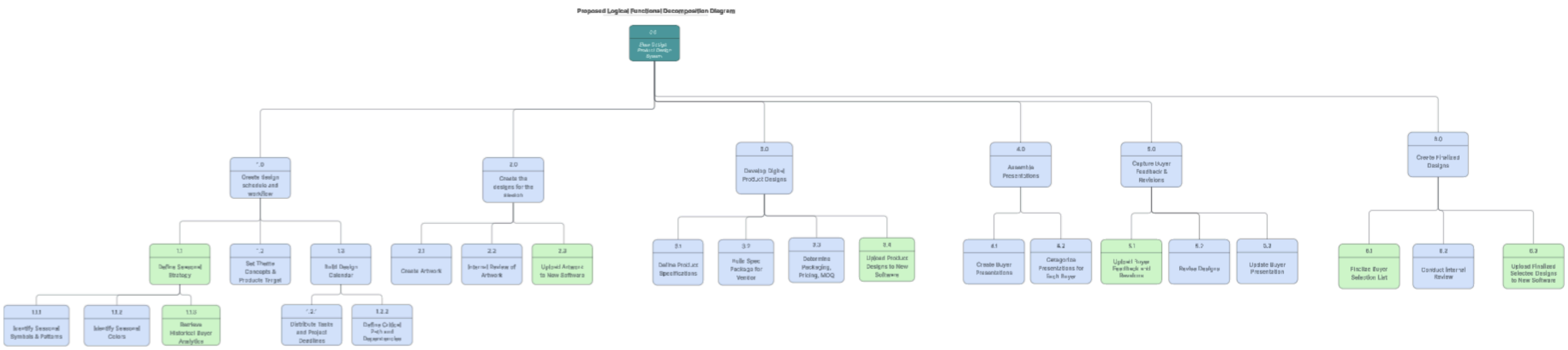


2. Proposed Logical Context Diagram

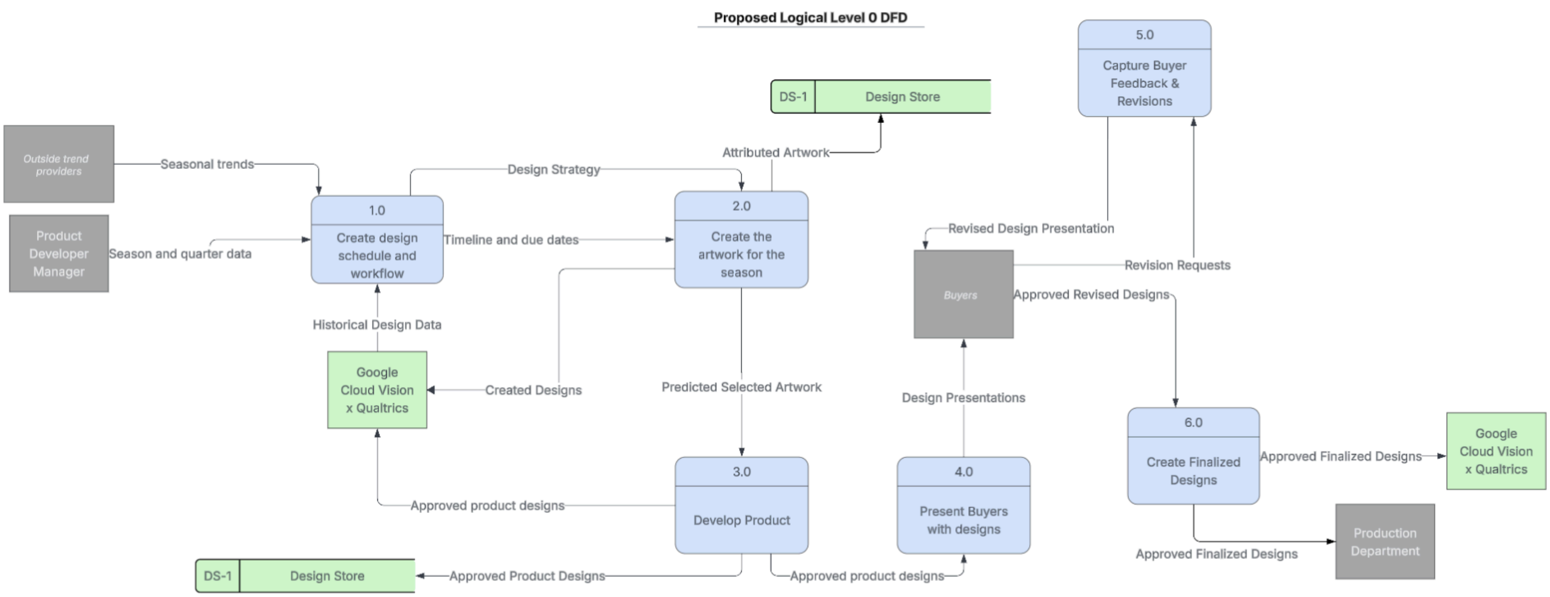




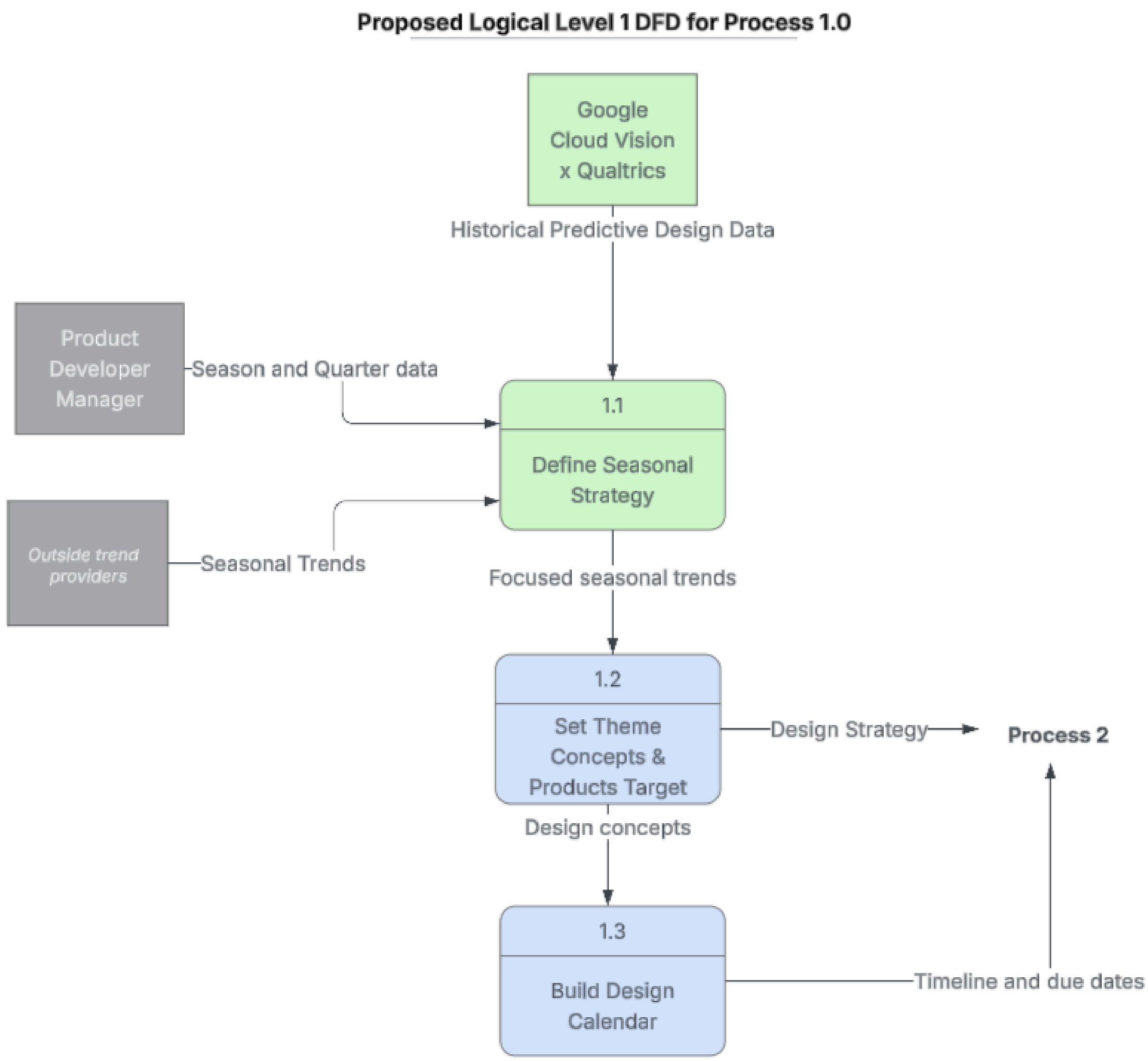
3. Proposed Logical Functional Decomposition Diagram



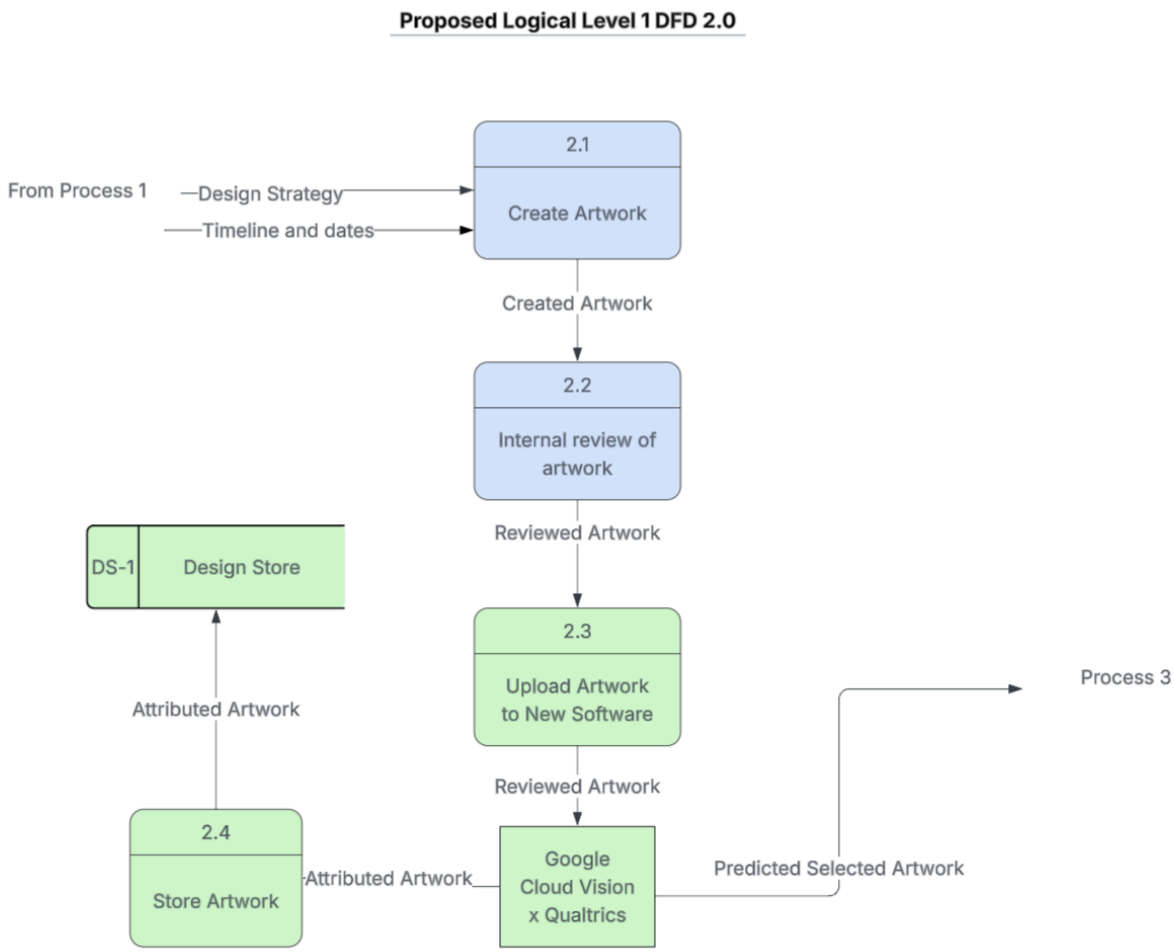
4. Proposed Logical Level 0 DFD



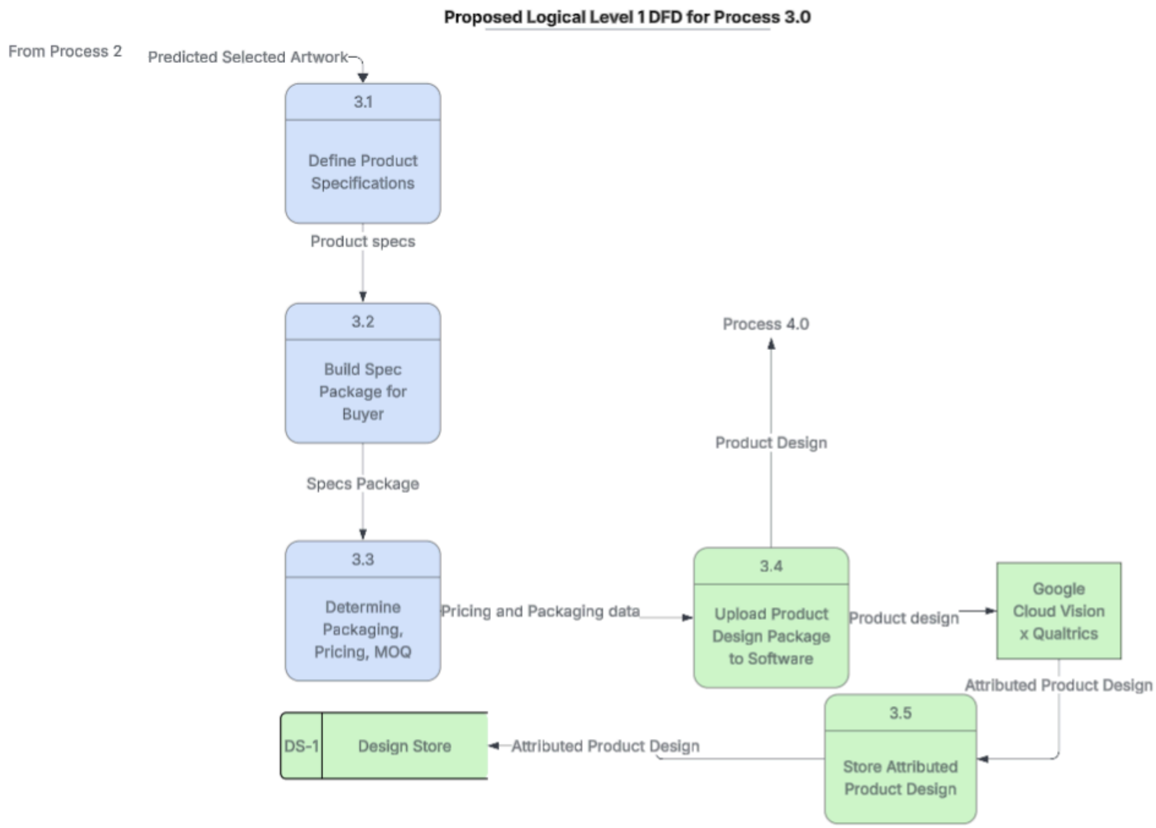
5. Proposed Logical Level 1 DFD for Process 1.0



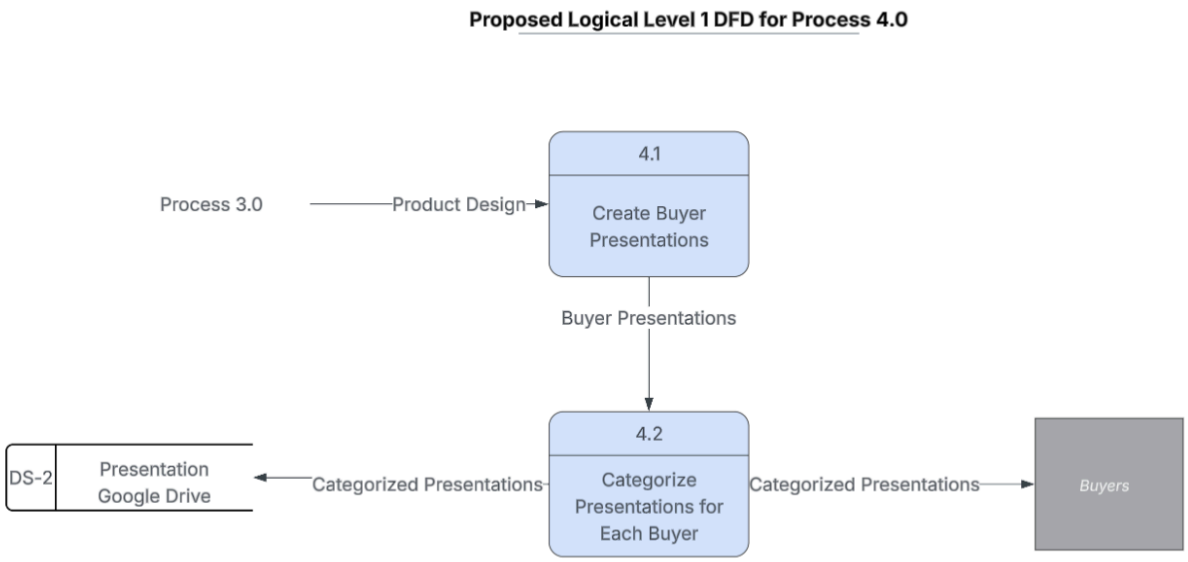
6. Proposed Logical Level 1 DFD for Process 2.0



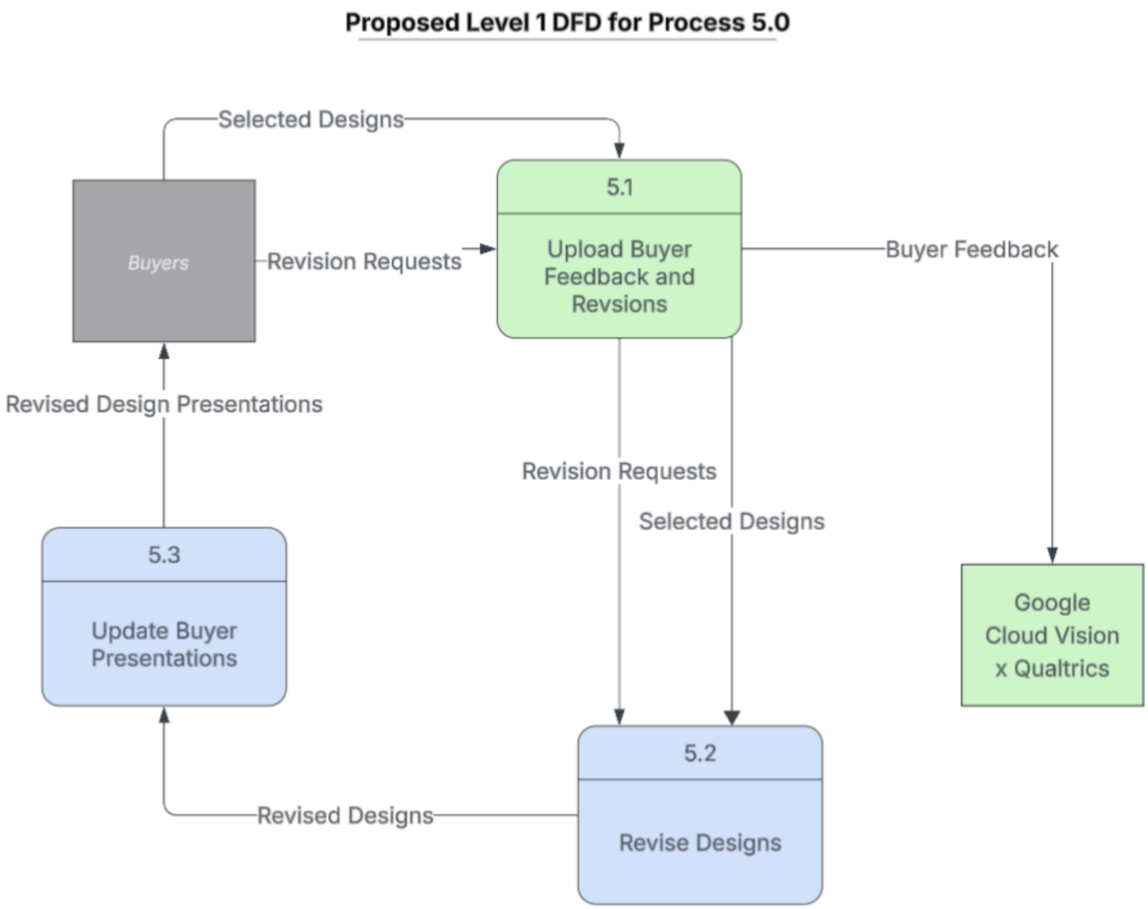
7. Proposed Logical Level 1 DFD for Process 3.0



8. Proposed Logical Level 1 DFD for Process 4.0



9. Proposed Logical Level 1 DFD for Process 5.0



10. Proposed Logical Level 1 DFD for Process 6.0

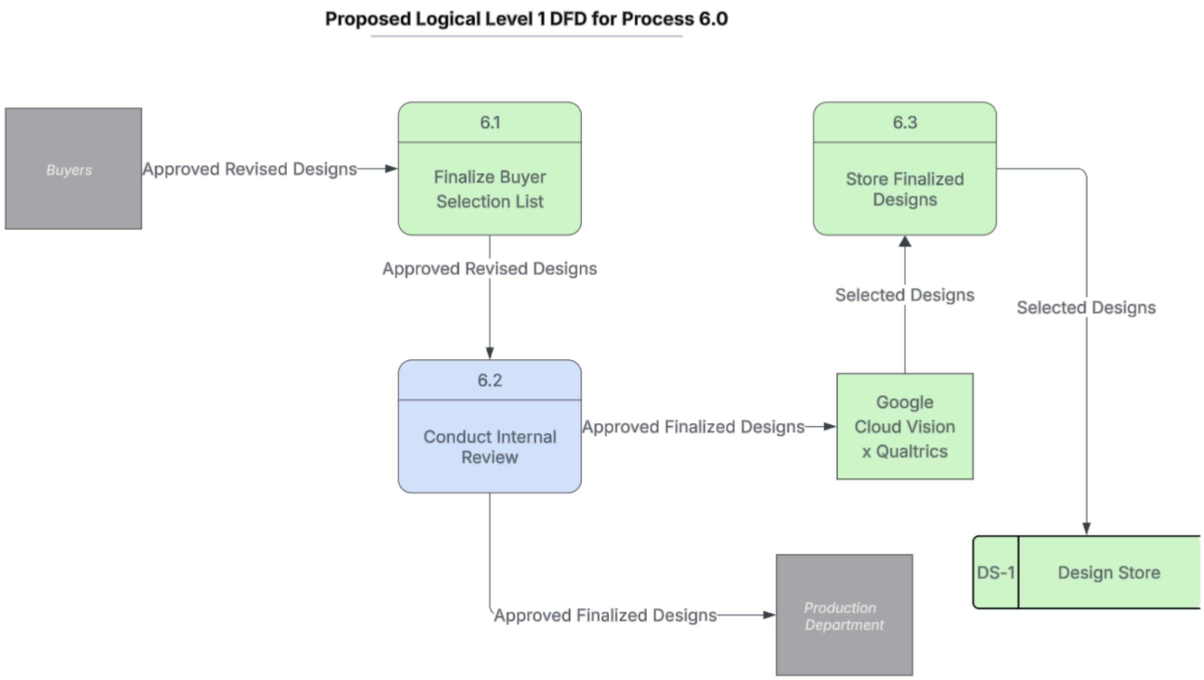
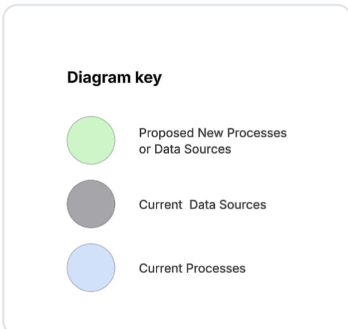
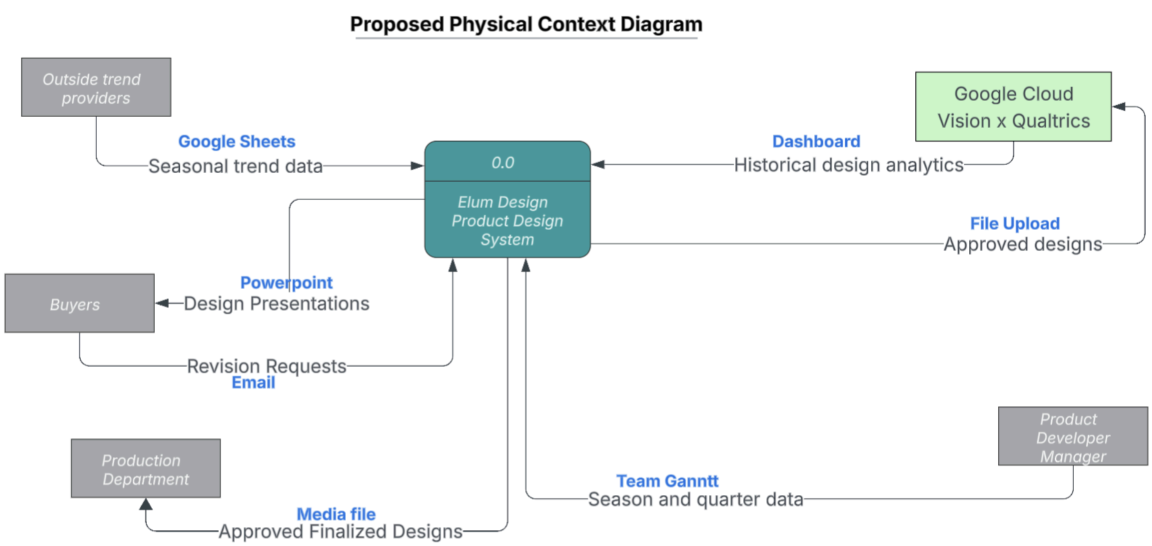


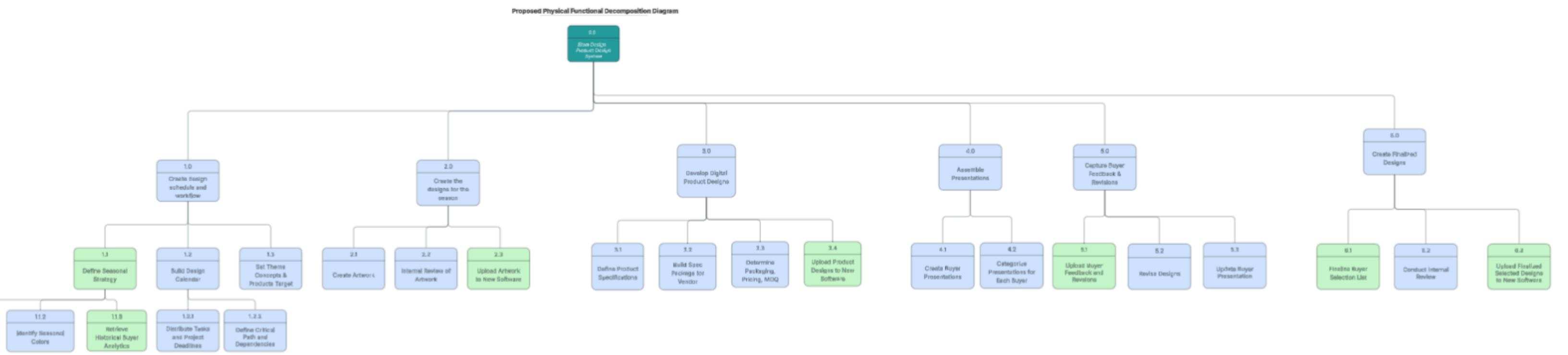
Exhibit E Proposed Physical Data Flow Diagram

1. Proposed Physical Context Diagram

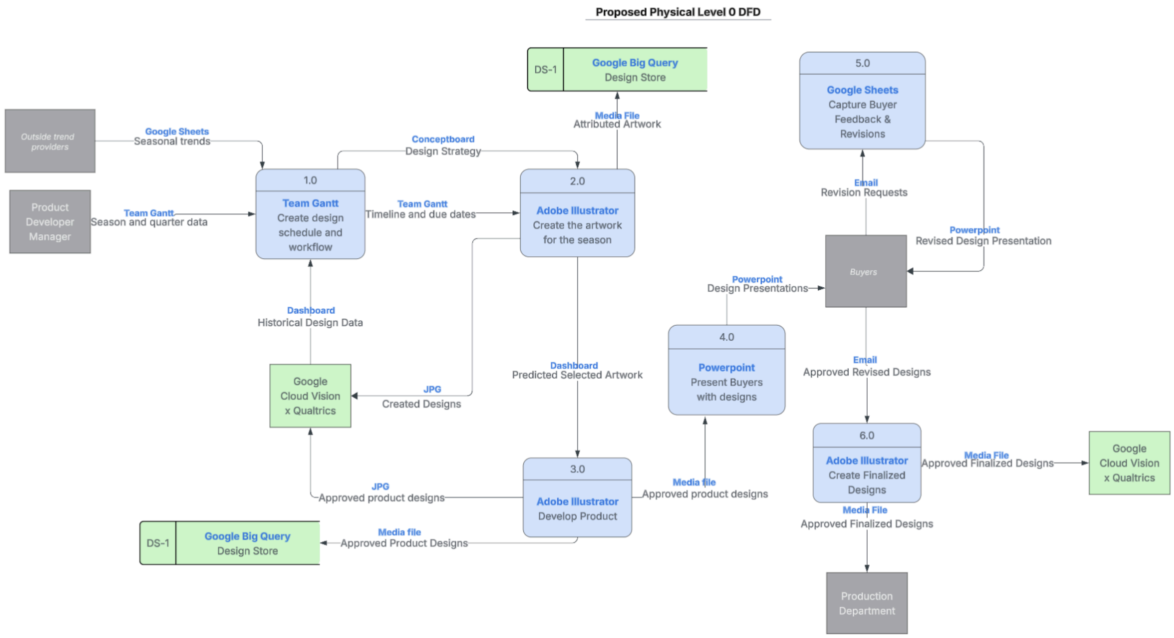




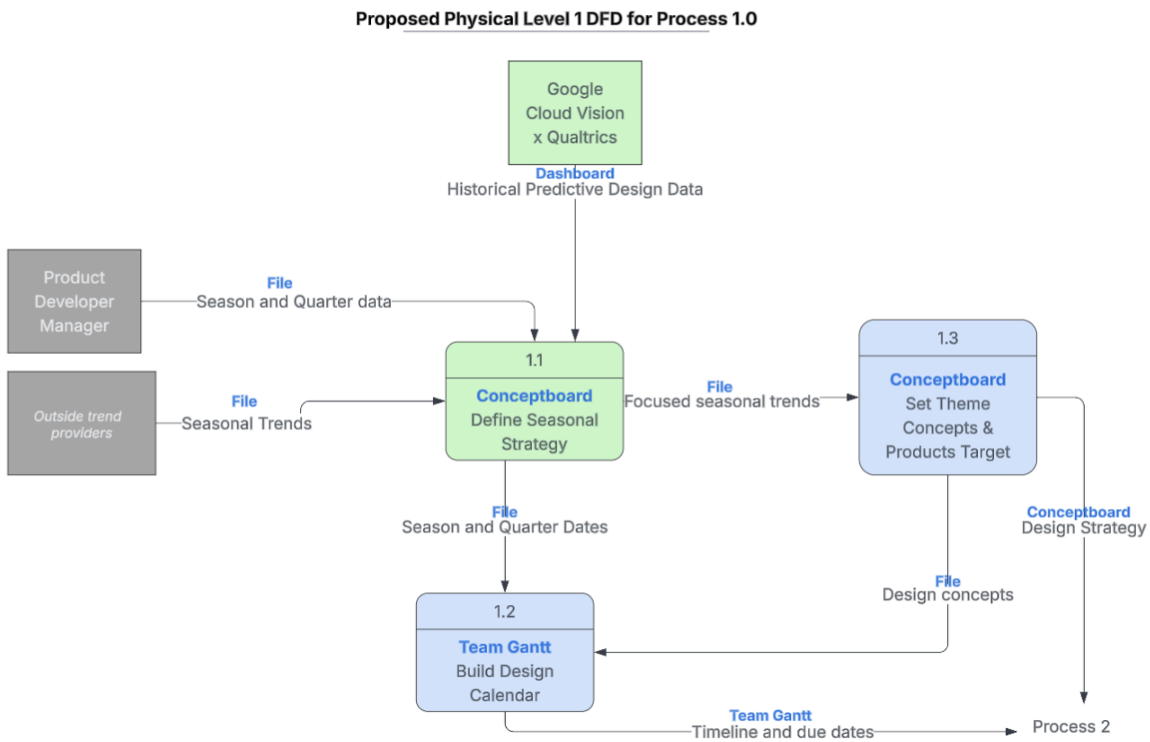
2. Proposed Physical Functional Decomposition Diagram



3. Proposed Physical Level 0 DFD



4. Proposed Physical Level 1 DFD for Process 1.0



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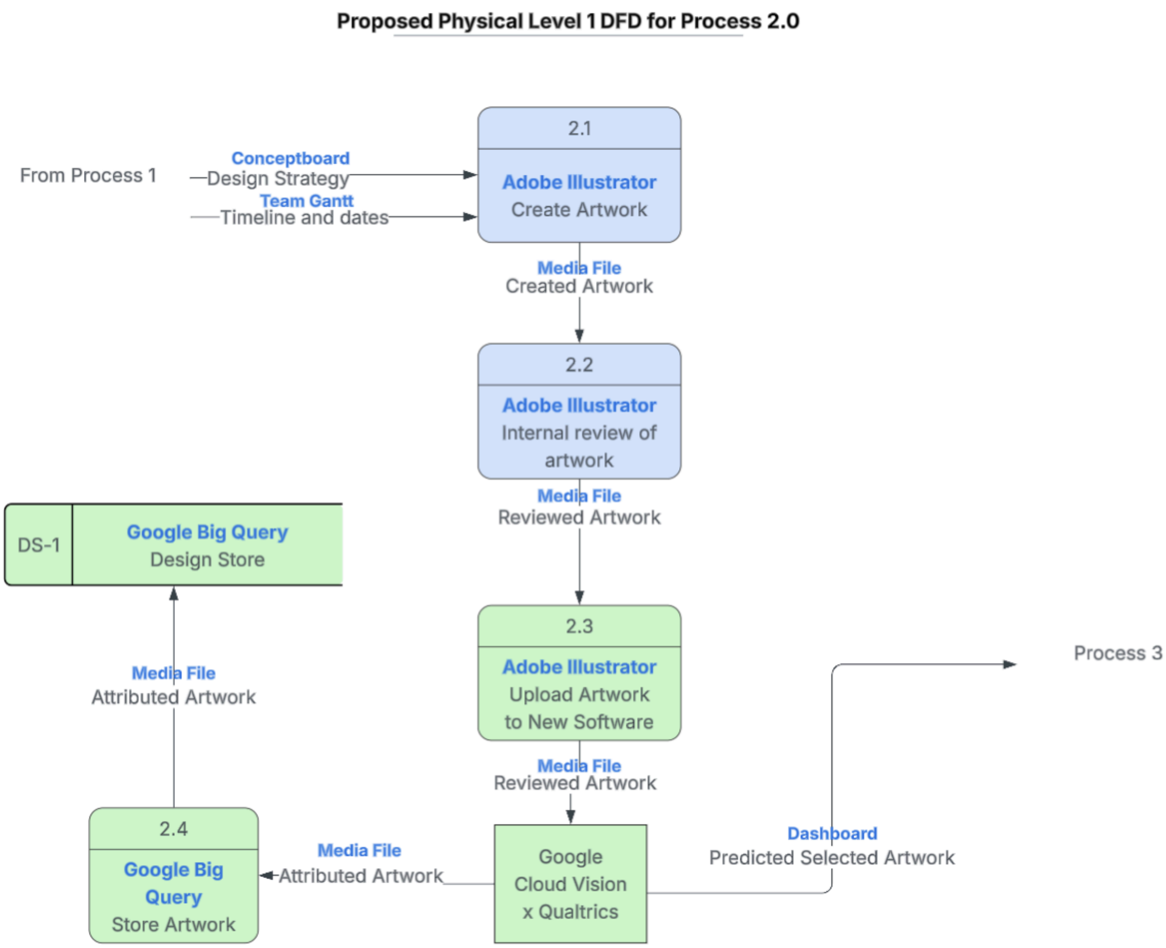
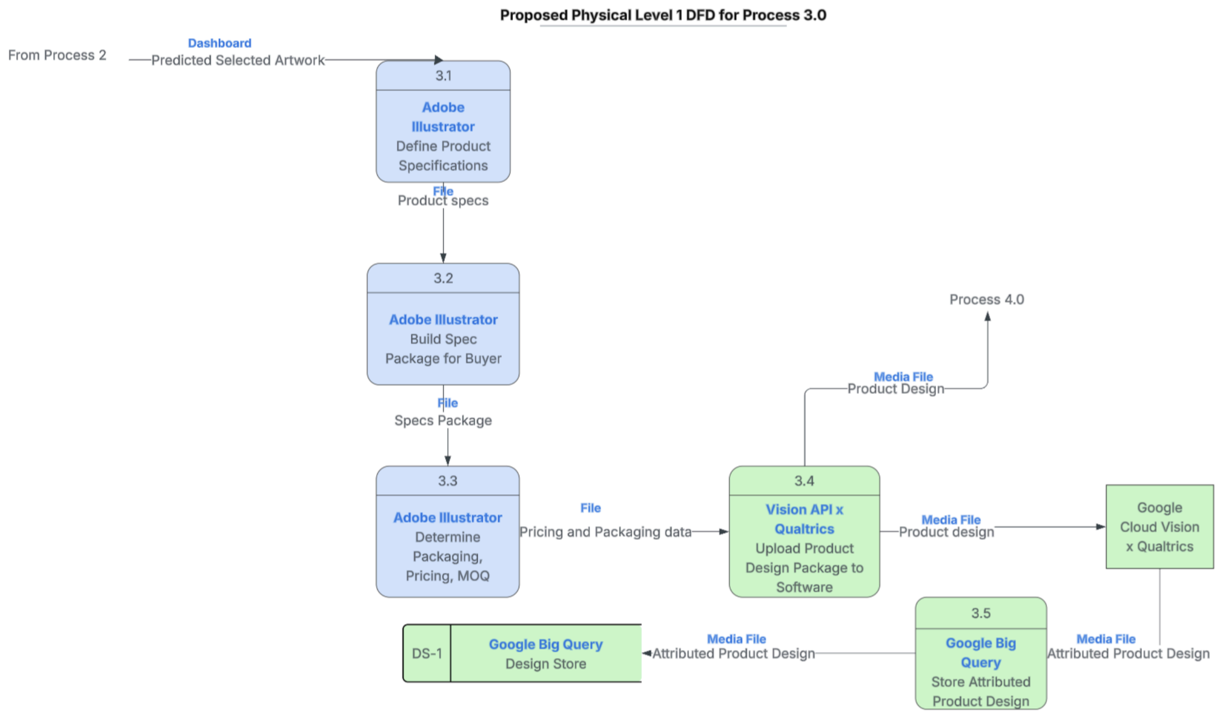
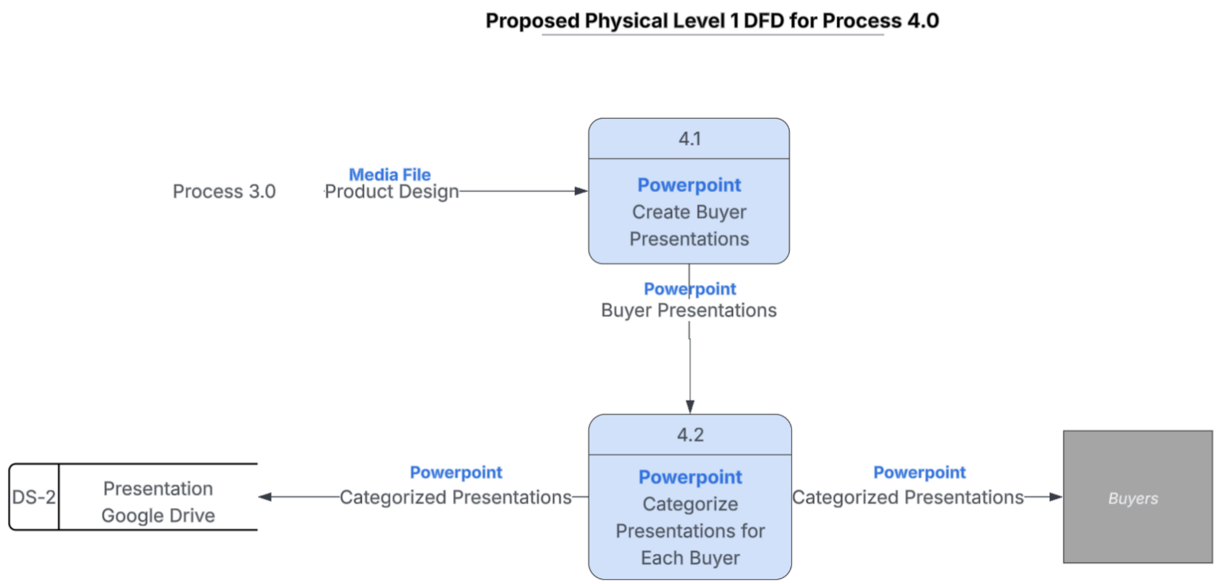


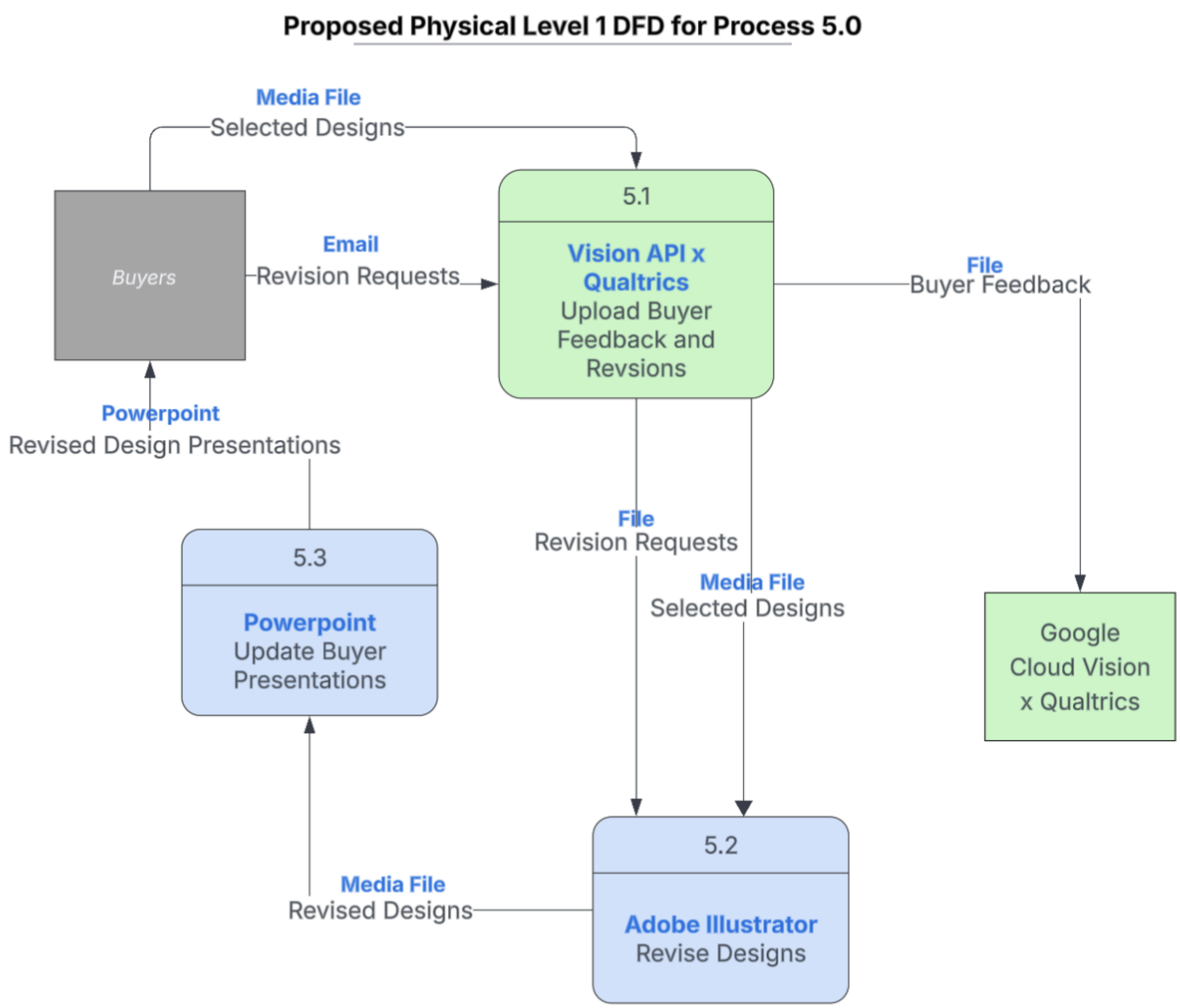
6. Proposed Physical Level 1 DFD for Process 3.0



7. Proposed Physical Level 1 DFD for Process 4.0



8. Proposed Physical Level 1 DFD for Process 5.0



9. Proposed Physical Level 1 DFD for Process 6.0

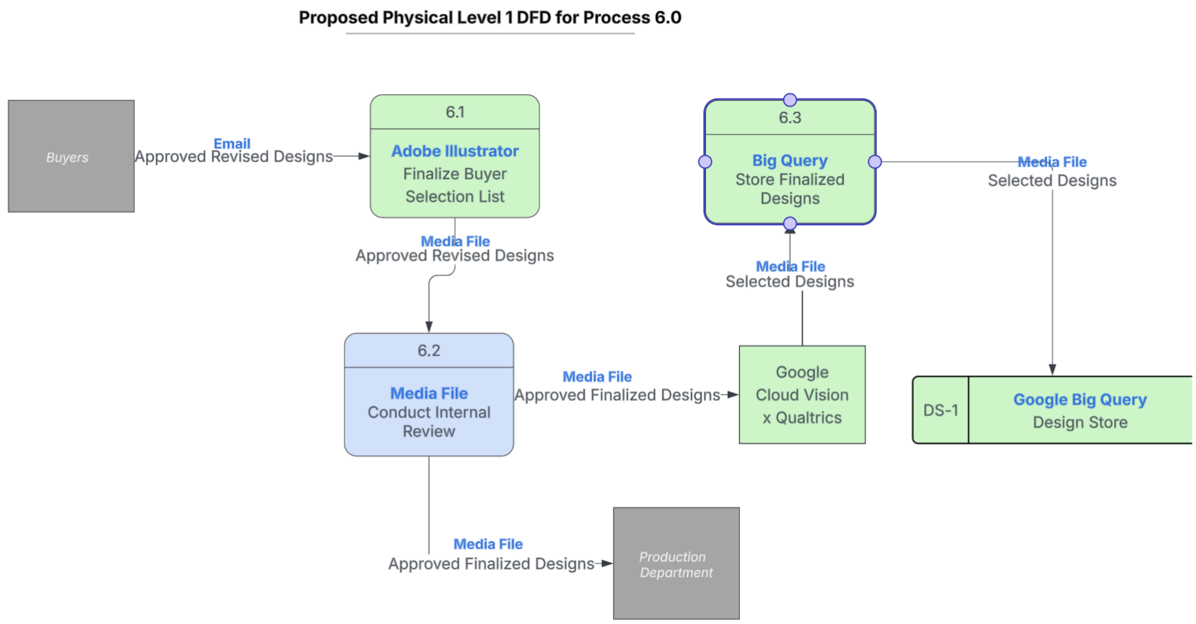
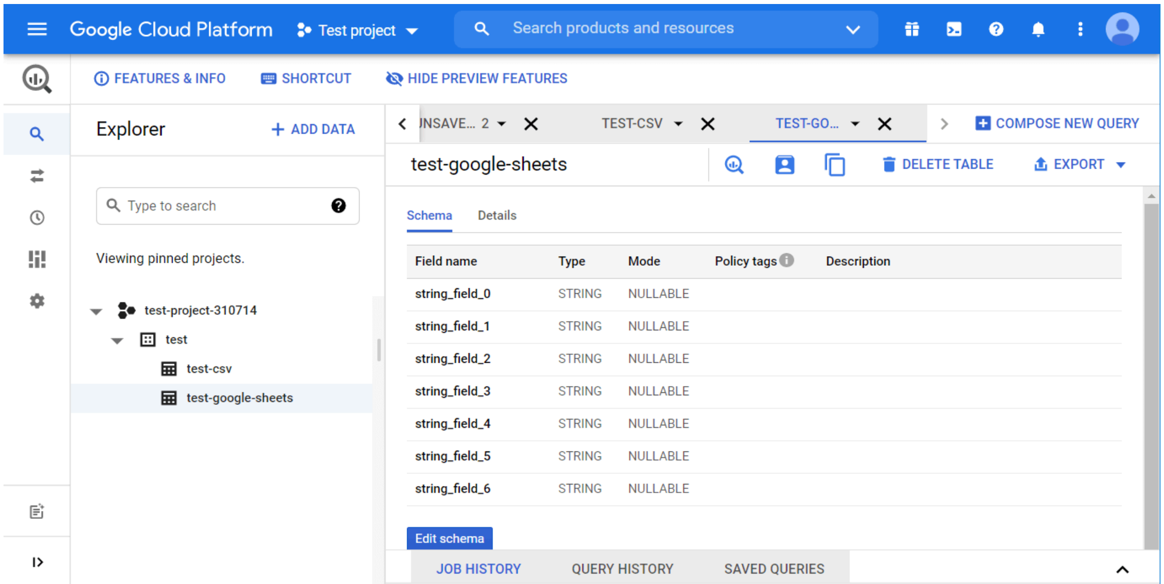


Exhibit F. ***Google Cloud Platform*** configuration for BigQuery and API access, GCP console showing a BigQuery dataset/table schemaand the APIs & Services → Credentials screen where an API key is created for the project.



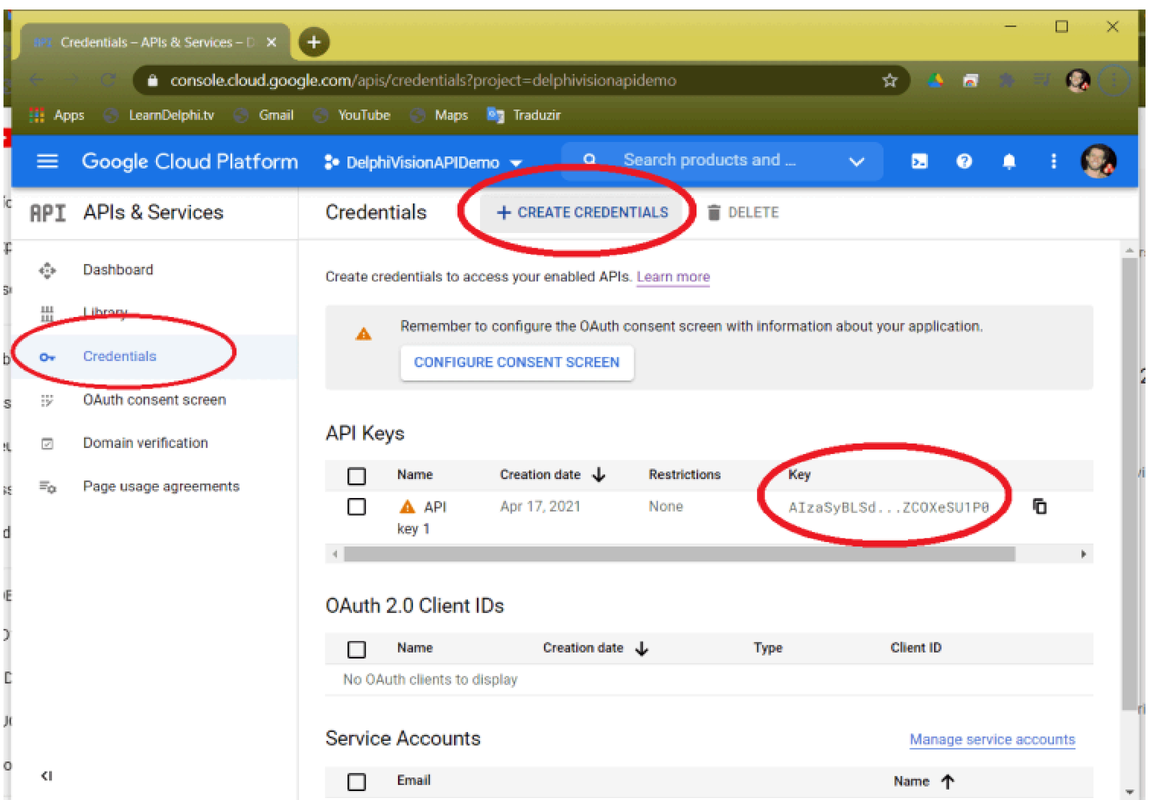


Exhibit G. ***Qualtrics CoreXM*** project creation screen Qualtrics CoreXM “Create a project” view used to start a new survey project for design concept testing**.**