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Optimizing Managerial Decisions in Marketplaces Using DSS

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Abstract. *The article examines the implementation of a decision support system (DSS) in a marketplace company as a strategic tool for moving from fragmented analytics to integrated, end-to-end management of data, predictive models, and business rules. Based on the materials of a dissertation study, the paper reworks the project logic of a target DSS designed for a platform-based business environment.*

The proposed system covers three key decision-making areas: dynamic pricing, inventory management, and personalization of user search results. These areas are considered not as isolated functional modules, but as interconnected components of a unified managerial decision loop. Particular attention is paid to the calculation component of the project, including the assessment of the annual economic effect, investment costs, net present value, three-year return on investment, and payback period. The analysis demonstrates that an integrated DSS can generate not only direct financial benefits, but also a broader managerial effect. This effect is achieved through shorter decision-cycle times, more consistent KPI interpretation, improved coordination between departments, and a reduced share of manual adjustments in operational processes.

The scientific and practical significance of the article lies in interpreting DSS not merely as an IT solution or analytical dashboard, but as a managerial infrastructure of the marketplace. Such infrastructure connects forecasting, optimization, organizational responsibility, and performance control. The findings suggest that the successful implementation of DSS requires not only technological readiness, but also data governance, transparent business rules, and clear ownership of decisions. Therefore, DSS becomes a mechanism for increasing both economic efficiency and managerial maturity in digital platform companies.

Keywords: *decision support system, marketplace, decision intelligence, dynamic pricing, inventory management*

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Marketplace-lərdə DSS vasitəsilə idarəetmə qərarlarının optimallaşdırılması

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Xülasə. *Məqalədə marketplace şirkətində qərarların dəstəklənməsi sisteminin (DSS) tətbiqi parçalanmış analitikadan verilənlərin, proqnozlaşdırıcı modellərin və biznes qaydalarının inteqrasiya olunmuş, tam dövri idarə edilməsinə keçid üçün strateji alət kimi araşdırılır. Dissertasiya tədqiqatının materialları əsasında platforma tipli biznes mühiti üçün nəzərdə tutulmuş hədəf DSS layihəsinin məntiqi yenidən işlənmişdir.*

Təklif olunan sistem qərar qəbuletməsinin üç əsas istiqamətini əhatə edir: dinamik qiymətqoyma, ehtiyatların idarə olunması və istifadəçilərin axtarış nəticələrinin fərdiləşdirilməsi. Bu istiqamətlər ayrı-ayrı funksional modullar kimi deyil, vahid idarəetmə qərarları dövrünün qarşılıqlı əlaqəli komponentləri kimi nəzərdən keçirilir. Layihənin hesablama komponentinə xüsusi diqqət yetirilmişdir ki, bura illik iqtisadi effektin, investisiya xərclərinin, xalis cari dəyərin (NPV), üçillik investisiya gəlirliliyinin (ROI) və geriödəmə müddətinin qiymətləndirilməsi daxildir. Təhlil göstərir ki, inteqrasiya olunmuş DSS yalnız birbaşa maliyyə faydaları deyil, həm də daha geniş idarəetmə effekti yarada bilər. Bu effekt qərar qəbuletmə dövrlərinin qısalması, KPI göstəricilərinin daha ardıcıl interpretasiyası, şöbələrarası koordinasiyanın yaxşılaşması və əməliyyat proseslərində əl ilə edilən düzəlişlərin payının azalması hesabına əldə olunur.

Məqalənin elmi və praktiki əhəmiyyəti DSS-in yalnız İT həlli və ya analitik panel deyil, marketplace-in idarəetmə infrastrukturu kimi şərh edilməsindədir. Belə infrastruktur proqnozlaşdırmanı, optimallaşdırmanı, təşkilati məsuliyyəti və fəaliyyətə nəzarəti birləşdirir. Tədqiqatın nəticələri göstərir ki, DSS-in uğurlu tətbiqi yalnız texnoloji hazırlıq deyil, həm də məlumatların idarə olunması, şəffaf biznes qaydaları və qərarların qəbuluna görə aydın məsuliyyət bölgüsü tələb edir. Beləliklə, DSS rəqəmsal platforma şirkətlərində həm iqtisadi səmərəliliyin, həm də idarəetmə yetkinliyinin artırılması mexanizminə çevrilir.

Açar sözlər: *qərarların dəstəklənməsi sistemi, marketplace, decision intelligence, dinamik qiymətqoyma, ehtiyatların idarə olunması*

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Introduction

The appearance of marketplaces on the retail e-commerce scene has brought changes in the format of making managerial decisions. Information available to classic retail managers on a periodic basis, through the manager's experience and regular product flow – has been substituted by information stream coming to platform managers on an ongoing basis: from search queries to sellers' comments on promotions. This information flow includes a vast array of data presented in different formats: clicks, product cards, available volumes of products in stock, delivery terms, competitor's prices, customer reviews, information about returns and a variety of other parameters. The crucial resource of an online marketplace is not just the mass of transferred data, but the ability to process information in real time and make economic decisions that bring benefit to all participants of the platform, without compromising their interests.

In today's competitive retail environment, Strategic Decision Support Systems (DSS) are increasingly important. DSSes don't exist to substitute managers but to provide a more informed, reproducible and verifiable decision process where possible. For a marketplace, price, offerings and search results all form an interwoven system where a simple increase in price could lead to higher demand whilst putting warehouse(s) under greater pressure to fulfill orders. A promotional manoeuvre that increases conversion rates may also increase returns for some products. Optimizing inventory to reduce losses in one area of the business may require coordination with other functions such as forecasting and marketing. As such, the most advanced DSSes support not one but multiple decision processes that need to be aligned in order to make optimal business decisions.

This article is the continuation of the author's previous study on developing an independent scientific and practical interpretation of the results of the dissertation study, and on developing a calculation model for determining the effectiveness of implementing an integrated DSS in a marketplace company. The article differentiates from the dissertation text in organization of material. Unlike in the dissertation text the material was organized according to chapters of a qualification paper, in this article it is organized in accordance with a journal publication logic, namely, after formulating a problem, one describes a methodology, then develops solution architecture, implements an algorithm, and finally shows economic result (Ecommerce Europe, & Amsterdam University of Applied Sciences, 2024; European Commission, 2026; MacKay & Weinstein, 2022).

What are the conditions for the implementation of DSS in the marketplace to be economically efficient? How to achieve the calculated effect in practice? To answer these questions, it is necessary to combine the technologies, organizational and financial analysis. The article discusses conditions for implementing DSS in the marketplace and corresponding mechanisms to achieve calculated efficiency, analyzing models, ROI, and technical architectural elements - the elements without which efficiency is formal.

Research

The article is based on case-oriented modeling of a large marketplace company as well as on calculated scenario for DSS implementation. This method is relevant in a situation when internal operational platform data are absent, but a viable evaluation model is needed. The calculation is not an audit of a particular company, but rather it is illustrated with real economic logic, typical for large marketplaces with developed logistics, advertising and analytical environment. The empirical logic of unified DSS, therefore, consists of three levels of analysis: First, the problems of the current DSS-loop are elaborated on, including the use of fragmentary metrics, delays, low connectivity among pricing, inventory, and personalization, as well as low transparency of manual adjustments. Second, a vision for a target DSS is concretized by elaborating on several layers and organizational roles needed to achieve these objectives. Third, the effects are concretized for key areas such as margin by pricing decisions, avoidance of inventory losses, contribution of personalized ranking, and savings in organizational time.

Using standard investment analysis methods (ROI, NPV, payback period) to assess DSS' investment efficiency. In addition to that, an attempt is made to calculate the managerial benefit received from using DSS – not just in terms of cash flow, but also in terms of quality of management and control (not immediately reflected in financial statements) – such as shortening the decision cycle, aligning KPIs, tracking number of overrides etc.

The methodology is characterized by a cautious attribution of the effect. Every improvement in the margins or conversions by the DSS cannot be attributed solely to the DSS, as other factors – such as market conditions, seasonality, team actions or assortment – may have contributed to the improvement. As such, the calculation is based on the principle of a verifiable effect, i.e. first the potential size of the improvement is determined and then an attribution coefficient or a conservative rounding is applied in order to ensure the stability of the developed model and to avoid overestimating the results.

Diagnosis of the Managerial Problem. There are already a wealth of data and an array of analytical tools at your disposal. What you can't have is time to set everything up from scratch. This means that you don't need to start entirely from scratch. Unlike many retailers, you won't have to build an entire data organization from the ground up. Instead, you can build on what is already there, improving it to overcome existing issues such as analytical abundance unbacked by managerial consistency. Reports, models and dashboards will already exist but different parts of the organization will have different versions of the 'truth' – different KPIs driving different perspectives on the same activity (Ailawadi & Farris, 2017; Gupta et al., 2022; Stalidis et al., 2023). Commercial, Supply Chain, Marketing, Product and Finance all want to make better decisions faster. They need help to collaborate and to agree on the true attribution of results.

The riskiest overlap is among three parts of the stack: pricing, inventory and personalization. Framed this way, each module can seem locally optimal while harming overall performance. The pricing module might shine by offering a better price and increasing sales, only to not realize the risk when inventory runs low. Personalization might seem brilliant when it gets your products in front of users most vulnerable to your weaknesses – though that's not the same as most reliable to buy from you. And while the warehouse logic will say that your stacks are at the perfect level, the promotional logic might say, "we need to have more of those on the shelf!" or the advertising logic might say that traffic is down this month, so you must discount more. Managing these parts of the stack separately robs your platform of profit, hurts your customers' experience, and wastes the time of your best managers. The second problem with taking a longer time to act on an analytical conclusion is that insights have a limited shelf life in an extremely dynamic platform. In the time it takes to transfer a decision into the business process, the insight could have lost its economic value. This is especially the case in a marketplace environment where demand, competitor's prices, product availability and seller behavior are all constantly changing. Therefore, the DSS must include a prediction component as well as an activation component. The prediction component develops alternative plans, and the activation component is responsible for executing those plans by translating the decisions into appropriate interfaces, APIs, or a rule-based engine.

Insufficient transparency of interventions. As mentioned earlier, managers have to override some of the model recommendations due to several reasons like missing variables in the dataset that come to their notice only after the model has been deployed and they have started observing the actual impact of the interventions in the context in which the model was deployed. While this is not a problem in itself, as managers are required to handle exceptions and intervene manually when required, the issue arises when the intervening actions are not logged and analyzed for the system to learn from the reasons of the deviations. Similarly, it is important for the organization to know which rules are actually working. Hence, a mature DSS should capture not only the automated decision but also the manual override, the reason for it and the ultimate outcome.

Table 1
Main gaps in the marketplace decision-making loop.

Problem area	How it manifests itself	Risk for the marketplace
KPI fragmentation	Different departments use inconsistent definitions of margin, conversion, stock-out, and seller quality	Disputes over figures, delayed decisions, weak attribution of effect
Gap between loops	Prices, inventory, and search results are optimized as separate services	Locally correct actions create systemic losses
Slow transition from analysis to action	An insight is not embedded in the production process or requires lengthy coordination	Lost demand, increased manual work, lower response speed
Opaque override actions	Manual adjustments do not have a standardized log or reasons	Loss of learning effect and growing dependence on experts

Source: Compiled by the author

Target Architecture of the Integrated DSS. My approach is to create an end-to-end integrated DSS decision solution for management. Unlike traditional DSS which was departmentally designed, all decisions in this model are integrated together following a chain of data - forecast - optimization - business rules - action - performance control. Similarly, for each decision, specific guidelines must be created for input data, recalculation frequency, analytical model, business rules, person responsible for decision result, degree of permissible automation and fallback procedure. Unlike typical managerial DSS, the outcome will be fully integrated data mart with advanced analytical capabilities – information or big data warehouse.

For concreteness and organization, one might organize these layers in the following architecture: 6 Levels of Forecasting Including Optimization Architecture. This architecture includes Data foundation consisting of the lakehouse and unified directories of users, products, sellers, orders and warehouse / fulfillment units. The second level consists of a semantic layer / feature store that formally fixes the common set of features. The third level consists of predictive forecasts of several quantities: Demand (DTF), Click probability (CTF), Conversion probability (CTF), Return probability (RTF), Delivery in time (ONTF), and Shortage risk (STF). The fourth level of optimization / rule creation transforms the above forecasts into a set of actions with corresponding values while respecting marginal and service costs as well as inventory and other operational constraints, and adherence to company / platform policies. The fifth level of activation consists of APIs, general purpose dashboards / user interfaces and the rule engine that will be used by the retailers / sellers and channel managers to configure the rules that are executed behind the scenes. The sixth level of monitoring and governance is responsible for: data quality; model drift over time; results of experiments run using the forecast and resulting uplift; and impact of managers.

Within the dynamic pricing loop, the DSS must not only generate a recommended price, but also compute the economic result, considering factors of demand, cost, competition and risk of negative consequences. The choice function for such a problem can be formulated in general form as the maximization of the expected margin minus penalties for sharp price movements and for assumed risk, $\Pi(p) = (p - c)D(p,x) - \lambda\Delta p - \varphi R$. This means the platform owner should not over maximize for short term gains that may erode consumer trust, generate higher returns for some parties, or breach price corridors for existing brands.

There is demand in the marketplace created by the platform itself. Therefore, classical Reorder Point has to be reinforced with signals from Marketing activity, Promotion plans and the results of personalized traffic on the platform. This will allow to avoid creating an artificial shortage in the market (Verhoef et al., 2021). Additionally, the module of inventory management can benefit from the signals coming from pricing and personalization and as a result, the module can dynamically adjust variables such as replenishment time, safety stock levels or a strategic placement of goods across the warehouses before there is actual demand from the marketplace.

While optimizing the personalization loop typically involves ranking by click probability, for a marketplace it is valuable to apply a multi-criteria approach. In addition to click and conversion probability, the expected margin contribution and return risk must be taken into account. Seller quality and a strategic diversity coefficient should also be incorporated. This logic for ranking serves to avoid "empty engagement" where users click on product cards but provide no sustainable contribution to the platform economy.

Implementation Algorithm. As appealing as it might be to launch an optimally designed DSS, even such a tool will yield no benefits if it is launched as simply another IT system. In a market, DSS implementation represents a fundamental organizational change that in turn transforms a number of key performance metrics, redefining the authority and roles of individuals and institutions at various levels of the organization, altering key regulations that must be complied with, and even fundamentally transforming the mode of management. Gradual integration of these innovative tools into routine practices is therefore key. A good first step in this process is formalization of key decision points; That is, someone should specify where, how often, and what decisions are made (price, inventory levels, search results), by whom, what are the potential costs of error, and so forth.

Step 2 – Second Stage – "Semantic Layer + Data Governance". Define unified semantics (definition of key objects) - user, order, seller, SKU, session, return, fulfilled orders, margin and other objects. Assign data owner for each object and a set of quality checks for his/her object. Step 3 - Third Stage - "Model Services + Feature Store". Start with few high-potential services - demand forecasting, price optimization, ranking services/recommendation services etc. Each of such services should bring measurable results very soon, but at the same time it will lay foundations for future scaling. Fourth stage is the implementation of the orchestration layer, which is responsible for making decisions between loops. For example, if the model predicts a product shortage, the system must either stop promoting the product, or increase its price, or start its replenishment.

If the model shows that a product has a very high margin, but at the same time it has a high return risk, its promotion can be regulated. If a seller violated SLA, his product should not be displayed in search results equally to the offers of reliable sellers. The orchestration layer is what turns a number of models into a unified system of making decisions. The 5th stage of Pricing, Inventory and Personalization for faster time-to-market is piloting. Pricing: For some categories like apparel, Pricing simulations for new logic on comparable SKUs to measure the lift. Inventory: Compare uplift between pilot categories by stock-out level and turnover. Personalization: Online experiment on CTR, conversion, margin per session, returns, and diversity. It is not enough to measure just the positive uplift.

One also needs to assess any side effects. Most important, the success of the pilot should be confirmed by the economic results (i.e., growth in the model) and not by the growth of some technical metric. Scaling and institutionalization of the DSS is the 6th stage. The DSS needs to be integrated into MLOps processes, continuously monitor, plan updates, document manual tweaks in logs, and governed by a governance council.

Similarly, for the DSS to be successful, there is a need to clearly define 3 roles within the organization such as business owner (responsible for financial outcomes), model owner (responsible for model performance/quality/ features) and platform owner (responsible for delivering decision to operations). If not, DSS turns into a toy for business to play with from time to time.

Table 2
Stages of DSS integration into marketplace architecture

Stage	**Content**	**Expected result**
1. Decision map	Fixing decision points, cycle frequency, owners, and the cost of error	A clear implementation scope
2. Semantic layer	Unified KPIs, reference directories, and data-quality rules	One version of managerial truth
3. Model services	Prediction, pricing, ranking, and feature store	Applied basis for the DSS
4. Orchestration	Model coordination, rule engine, arbitration	Alignment of prices, inventory, and search results
5. Controlled launch	Pilots, A/B tests, and control of side effects	Confirmed business effect
6. MLOps and governance	Monitoring, model versions, and owner matrix	Stable operation

Source: Compiled by the author

Calculation of the Economic Effect. The calculations are based on the assumption that the DSS is first implemented on a so-called pilot-loop covering the major decision categories, and thereafter gradually expanded to the full scope of the marketplace (Byrne & McCarthy, 2020; Ozon Holdings PLC, 2025; Zhang & Chen, 2020). Therefore, the impact is distributed over time. In the first year only a part of the potential gains is realized; in the second year a larger part will be realized; and in the third year the system will work on its optimal level.

The first source of effect is dynamic pricing. The annual GMV of the pilot loop is 13.030 billion AZN, and the initial contribution margin is 8.5%. The baseline contribution is 1.108 billion AZN*8.5% = 94.68 million AZN. If the DSS increases the realized margin by 0.45%, the new contribution will be 1.166 billion AZN*9.0% = 105.04 million AZN. The potential difference is 58.633 million AZN. This figure, however, cannot be verified by the platform. Therefore, with a cautious attribution, 35% of this improvement can be assigned to the system. As a result, the verifiable annual effect of the pricing loop is 20.530 million AZN.

The second source of potential losses can be identified with inventory management. The losses from bad quality, inadequate pricing, misplacement, obsolete inventory and excess stock within categories of goods sold amount to 1.8% of losses from inadequate shortage prevention. Hence, with the total merchandise turnover in the retail outlets under consideration amounting to 9.517 billion AZN, such losses amount to 171.310 million AZN. Our model therefore assumes a 14% reduction in such losses, amounting to approximately savings of 23.983 million AZN. Given the nature of such losses and limitations in tracking and controlling relevant indicators (particularly those that can be affected by store managers in the short-run), the model applies a slightly conservative estimate of savings amounting to 22.660 million AZN.

Personalization of search results is another of the sources of operator's influence on the user's choice. If the new recommendation logic is supposed to account for 30 % of the commercially significant traffic (98.1 mln. requests) generating income of 4 305 000 000 AZN, then the baseline contribution of the new logic would equal 387 486 000 AZN. Its increase of 4.8 % would bring an effect of 18 604 000 AZN.

Allowing for the uncertainty of experimental measurements, the latter parameter should be considered equal to 16 768 000 AZN. The additional effect of organization's work in the target mode consists in the lack of manual coordination in formation of search results and reduced analytical activity of users. Its sustainable effect equals 61 907 000 AZN, which in the financial calculations is rounded to 61 862 000 AZN.

Table 3
Calculated annual effect of DSS implementation

Effect area	**Annual effect, million AZN**	**Economic nature of the effect**
Dynamic pricing	20.530	Growth of realized margin and more precise price management
Inventory management	22.660	Reduction of stock-outs, excess balances, and unnecessary transfers
Search-result personalization	16.768	Growth of contribution per session and basket quality
Organizational effect	1.949	Reduction of manual coordination and acceleration of decisions
Total	**61.907**	**Total verifiable annual effect**

Source: Compiled by the author

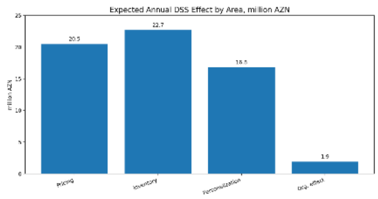

Figure 1
Structure of the expected annual effect by area.

Source: Compiled by the author

Investment Evaluation of the Project. For the project evaluation, the following parameters were used: initial investment I_0 = 26.059 million AZN, two annual operating expenses OPEX = 7.704 million AZN, evaluation period - 3 years, discount rate - 15%. The costs included in the investment were the development of the integration layer, the integration orchestration engine, the feature store, the lakehouse loops, MLOps, interfaces to different systems, prototype experiments, training of users, and support for changes of processes at organizations (Chopra & Meindl, 2021). Operating expenses for maintenance and operation of models, engineering support, data quality control, and team development were also included.

Payback of the project effect is gradual. In the first year 55% of annual effect is realized; in the second year – 85%; in the third year – 100%. Accordingly, net flows after OPEX will be as follows: CF1 = (61.862 × 0.55) - 7.704 = 26.320 million AZN; CF2 = (61.862 × 0.85) - 7.704 = 44.879 million AZN; CF3 = (61.862 × 1.00) - 7.704 = 54.158 million AZN. Undiscounted accumulated flow becomes close to zero by the end of the first year and starts growing rapidly afterwards, i.e. there is a very short capital payback period.

Net present value of the project is calculated by the formula $NPV = \Sigma\ CFt/(1+r)^t - I_0$. Using r = 15%, for three-year period its value is approximately equal to 66.37 million AZN. Three-year gain without discounting (ROI3y) is equal to 201.9% (148.468 - 49.172)/49.172 × 100%. Even reducing expected effect for 20%, the project is still investment-attractive because margin growth, reducing of inventory losses and improvement of personalization have different source and partly they compensate each other. The stability of solution is evaluated in scenario approach. According to the conservative scenario annual impact of the project may make 44,187 thousand AZN due to low quality of the initial data, resistance of users, low efficiency of pilot implementation etc. The impact in the baseline scenario will make 61,862 thousand AZN and in the optimistic scenario – 75,911 thousand AZN. These three scenarios are the general model for assessment of real possibilities of DSS implementation. In addition to the DSS model the organizational governance discipline is important. If the latter is weak enough, even with good technical implementation of the model, the actual results of its implementation may be lower than the calculated ones.

Table 4
Investment parameters of the DSS project.

Indicator	Value
Initial investment	26.059 million AZN
Annual OPEX	7.704 million AZN
Target sustainable effect	61.862 million AZN per year
CF1 / CF2 / CF3	26.320 / 44.879 / 54.158 million AZN
NPV at a 15% discount rate	≈ 66.37 million AZN
ROI over 3 years	≈ 201.9%
Approximate payback period	around the first year of operation

Source: Compiled by the author

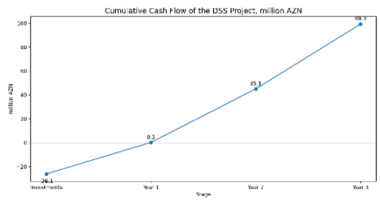

Figure 2
Cumulative cash flow of the DSS project.

Source: Compiled by the author

Managerial Interpretation of the Results. Though a number of financial metrics demonstrate that DSS project can be considered as an investment for the company, the managerial "return on investment" for a marketplace is much more than that. As described above, our solution substantially changes the approach to the control of the marketplace, allowing the management to see what really drives the GMV growth – whether it is actual demand, price, search quality, seller reliability or logistics.

Manager will no longer able to easily misunderstand KPIs when GMV growth looks good but margins decrease, return shares grow or the warehouse overload appears. An integrated DSS also reduces decision-making time. The system enables immediate proposing of actions and shows their expected results. Issues that are hard to explain and that occur occasionally are verified manually, but with the set of scenarios and justifications previously generated by the system. The manager's role is redefined from detailed micro-control to the management of rules, exceptions and boundaries between automated tasks. Long-term effect: accumulation of organizational knowledge. By storing all decisions, a company can not only assess the performance of a particular model, but also use the logged reasons for manual decisions to optimize business rules, tweak features and improve interfaces. Most important of all, the number of repeated exceptions should decrease over time. This positive effect can extend to the entire decision architecture in the long run (Bawack et al., 2022; Ricci et al., 2022).

A DSS serves the further function of helping to manage the trade-off between goals at the platform level and goals at the local level (e.g., different business units). Each stakeholder has their own goals. Marketing goals are to grow traffic. Commercial goals are to maximize margin. Logistics goals are to provide a stable and scalable fulfillment experience. Product goals are to drive conversion for specific product lines. Seller operations goals are to ensure sellers have a good experience on the site. These goals are often in conflict (Enholm et al., 2022; Sharda et al., 2021). An integrated DSS does not eliminate these conflicts, but helps to surface them, and manage them through a set of explicitly defined arbitration rules (e.g., weighting of various KPIs), and constraints on the optimization problem being solved.

Although the calculated effect of DSS for pricing on the basis of the seller is quite high, its implementation faces a number of difficulties. First, the quality of initial data is very important (Chen et al., 2022; Hidasi et al., 2016). If the lists of products, sellers, and warehouse units of sales are inconsistent, and events on sales arrive with considerable delays or errors, the DSS will mirror the errors of input information. Thus, data governance must become a priority before scaling up, and cannot be left to be a secondary task.

The second key risk is user resistance. Managers see the DSS as a threat to their own job functions, abdication of organizational responsibility, or unyielding management interference in what the manager regards as his/her area of control. To mitigate this risk, the DSS must be explainable at the business level. In addition to obtaining a DSS recommendation, the manager should see the underlying drivers (factors) that led to the recommendation. As an additional safeguard, the DSS should enable, justify, and make transparent and instructive to the system any instance of justified managerial override of the computer recommendation.

Thirdly, the risk of overestimating the effects needs to be addressed. Whilst the DSS will generate improvements in margin, conversion and turnover, not all of the result will be directly attributable to the system. This is due to a variety of reasons such as seasonality, changes in assortment and promotions, external factors, etc. To make the financial model as robust as possible, the results from the pilots need to be compared with the control groups. And an always conservative attribution to the DSS needs to be calculated.

The fourth limitation refers to the balance between automation and control in selecting and developing the target DSS. The marketplace cannot rely entirely on algorithms for making critical decisions, especially in branded categories, in scenarios involving external sellers, during periods of regulatory uncertainty, etc. Therefore, the marketplace needs to establish a system that can automatically make mass decisions while providing decision support in situations that are strategically significant or fraught with conflict.

Conclusion

The economic value of a DSS in a marketplace is not inherent in a single separate algorithm; it arises from the integration of data, models, business rules and organizational responsibility. Dynamic pricing, efficient inventory management and personalization of search results are key drivers of platform efficiency. However, maximum value is achieved when these levers operate as interdependent components of an integrated decision-making loop.

Investment attractiveness of the project is high. Using the calculation model, we obtained rather optimistic results – a target sustainable annual effect – about 61.862 million AZN, initial investment – 26.059 million AZN, annual operating expenses – 7.704 million AZN, NPV – 66.37 million AZN, ROI – 201.9%. The payback period of investments is about a year, which is good for such a large data/AI project of the platform company.

The main practical implication of the research for the DSS development is that its implementation should be viewed as marketplace controllability investment, and not as additional digital expense. The financial result of the DSS development is not the main result appearing in the organization's long-term period. Also very important is the periodic reduction of KPI fragmentation, quick decision-making and higher transparency of organizational decisions as well as acquisition of new knowledge by an organization.

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