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ARTIFICIAL INTELLIGENCE AS A DRIVER OF THE EVOLUTION OF UNMANNED AERIAL SYSTEMS AND THE EMERGENCE OF THE LOW-ALTITUDE ECONOMY

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Abstract:
This article examines the contribution of artificial intelligence to the evolution of unmanned aerial systems and the emergence of the low-altitude economy. Research on autonomous navigation and control is considered in conjunction with the economics of service delivery and digital coordination. Four economic mechanisms are identified: changes in labour requirements, reductions in repeat work, expansion of the service mix, and improved resource utilisation. An analytical expression for the cost per accepted result shows how utilisation and service quality shape the returns to AI adoption. The US UTM concept and the European U-space framework are compared in terms of coordination functions and information requirements. The analysis distinguishes intelligence at the aircraft level from ecosystem-level decision support. The implications point to the need for complementary investment in data, skills, infrastructure, and service organisation in Uzbekistan. No quantitative estimate of the effect on the national market is provided.

Keywords: Artificial Intelligence, Unmanned Aerial Systems, Low-Altitude Economy, Autonomy, Computer Vision, Machine Learning, Digital Ecosystem, UTM, U-Space, Productivity, Interoperability, Uzbekistan.

INTRODUCTION

The diffusion of unmanned aerial systems is changing the ways in which spatial data are collected, technical operations are performed, and small consignments are delivered. The economic significance of these changes depends on the ability to provide a demanded service repeatedly, at controllable cost and with consistent quality. For the digital economy, the key transition is from selling an aircraft and individual flights to establishing a reproducible process that integrates ordering, planning, execution, and the use of the resulting output. It is precisely at this transition that the contribution of artificial intelligence becomes important: which constraints does it remove, and which new dependencies does it create for market participants?

For Uzbekistan, the study is aligned with the objectives of the Strategy for the Development of Artificial Intelligence Technologies until 2030, approved by Resolution No. PP-358 of the President of the Republic of Uzbekistan dated 14 October 2024. The document provides for the development of data-processing infrastructure, specialist training, and the expansion of sectoral applications of AI [1]. In the context of unmanned services, these priorities require an integrated assessment of technology, demand, and information exchange. The purchase of equipment alone determines neither operator utilisation, nor the usefulness of the data collected, nor the ability of several organisations to provide a service jointly. Accordingly, research on UAS within the digital economy should explain the mechanism of value creation rather than being confined to equipment characteristics.

The article develops the proposition that AI affects the sector at two interrelated levels. At the level of an unmanned aerial system (UAS), it expands the capabilities of perception, adaptation, and task execution. At the level of the low-altitude economy - understood as the set of civil aerial services together with the supporting production activities, infrastructure, and digital interactions - AI supports resource coordination and the use of accumulated data. Service organisation is the link between these levels: a technological advantage acquires economic significance through the quality of the accepted result, full-cycle costs, and the ability of independent participants to execute orders jointly. The low-altitude economy is broader than unmanned aviation; this article focuses on its civil-UAS segment without imposing a universal altitude threshold across countries.

LITERATURE REVIEW

Research on autonomous UAS initially frames the problem as an interaction between aircraft capabilities and environmental constraints. Floreano and Wood examine the development of small autonomous drones

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through the relationship among design, perception, and conditions of use [2]. Importantly, autonomy is treated as a property of the system as a whole. This perspective helps avoid the common error of attributing all technological progress in unmanned aviation to a single algorithm. For economic analysis, it implies the need to distinguish the contributions of the hardware platform, conventional control systems, and learning-based components. A new payload may expand the range of services even without a change in the level of AI, whereas more accurate recognition may increase the value of a service delivered by the same aircraft.

Loquercio et al. investigate autonomous navigation in complex environments. Their approach converts observations from onboard sensors into trajectories using a neural network trained in simulation and demonstrates transfer to real, previously unseen environments [3]. Kaufmann et al. demonstrate the potential of reinforcement learning in the Swift system, which competes against professional pilots [4]. Both studies confirm an expansion of technically achievable capabilities, but they address different tasks. The former is particularly relevant to adaptation to complex environmental geometry, whereas the latter concerns control at the limits of dynamic performance. Their comparison shows why the label 'intelligent drone' is insufficient for evaluation: it is necessary to identify the function performed by AI and the conditions under which the result has been validated.

At the economic level, Yin, Chen and Wang analyse data from 30 Chinese regions for 2012-2022 [5]. They identify a statistically significant inverted-U relationship between AI development and a composite indicator of the low-altitude economy. This finding challenges the assumption of unconditionally increasing returns to technological investment. At the same time, the regional index combines several processes and does not directly measure the productivity of a particular operator. The result should therefore be used as a basis for examining heterogeneous effects rather than as a ready-made efficiency coefficient for any UAS project.

This heterogeneity can also be interpreted through the productivity J-curve discussed by Brynjolfsson, Rock and Syverson. The authors emphasise the importance of complementary intangible investment when adopting general-purpose technologies, including AI, as well as the resulting difficulties in measuring productivity [13]. In the present sector, this perspective highlights expenditure on data preparation, process redesign, and staff training. These activities precede stable operation and may not be reflected in the purchase price of the aircraft. Comparative assessment should therefore cover the entire service-production process and account for the time required to master the technology.

Jacobides, Cennamo and Gawer link the emergence of ecosystems to modularity and the specific complementarities among the activities of independent organisations [12]. Applied to the low-altitude economy, this provides a criterion that distinguishes an ecosystem from a simple list of firms: the output of one participant must be technologically and organisationally usable by others. Spatial data, for example, gain additional value when they can be integrated into the customer's sectoral process, while planning services become more valuable when operators of different aircraft can use them. Applying ecosystem theory to UAS therefore makes it possible to examine interoperability as an economic condition for the division of labour.

In the domestic literature, Umarova and Odilova consider the development of the digital economy in relation to infrastructure and digital competencies [6]. For Uzbekistan, this perspective is important because it draws attention to organisations' capacity to absorb technology. In unmanned services, competencies are required simultaneously for equipment operation, data processing, and interpretation of sector-specific outputs. A shortage of specialists is therefore not limited to the number of trained pilots; it may arise at the stages of image analysis, integration with information systems, or service-quality verification.

In their review of small UAS applications in precision agriculture, Zhang and Kovacs emphasise the importance of data processing and its connection with the needs of agricultural users [10]. Their work helps clarify the unit of economic output: it may be a decision concerning a field plot rather than the mere acquisition of an image. Taken together, the studies reviewed provide a basis for linking autonomy to the organisation of production and the market. Comparison across these strands reveals different units of analysis: technical research evaluates aircraft behaviour, economic research evaluates output or productivity, and ecosystem theory evaluates interdependence among organisations. Their integration reveals an intermediate mechanism: changes in aircraft functionality reorganise service delivery, while repeatable service delivery creates demand for interoperable infrastructure components.

RESEARCH METHODOLOGY

The study combines a critical review of scientific publications from 2012-2026, a functional comparison of technical results, and an economic interpretation of digital-coordination models. The evidence base comprises experimental studies of autonomous navigation and control, a regional study of the relationship between AI and the low-altitude economy, ecosystem theory, and official materials from the FAA, EASA, and LexUZ. Comparison is conducted at three levels: the UAS function being changed, the output of

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the production process, and the organisation of interaction among participants. Experimental indicators are interpreted within the conditions of the original studies; the cost framework and infrastructure relationships represent the author's analytical synthesis. Source selection is purposive and does not claim the completeness of a systematic review.

ANALYSIS AND RESULTS

FROM FLIGHT AUTOMATION TO AUTONOMOUS TASK EXECUTION

The evolution of UAS involves a transition from the automation of individual actions to autonomous task execution. An automated aircraft can maintain a specified altitude, follow a route, and perform a predetermined sequence of actions. Many such functions are implemented through navigation tools, controllers, and programmed rules. Autonomy implies a broader set of decisions within the assigned task: interpreting observations, selecting an admissible action, and adapting when conditions change. Learning-based algorithms expand this decision set but operate jointly with other system components. The level of autonomy should therefore be described in terms of functions and operating conditions rather than by the mere presence of an 'AI' label.

Under remote control, a human closes much of the perception-and-decision loop by evaluating imagery, recognising obstacles, and selecting manoeuvres. This arrangement provides flexibility through pilot experience, but it links the scale of activity to the availability of human attention. In a pre-programmed mission, workload may decline as long as the environment remains consistent with the initial assumptions. An unexpected obstacle, a change in visibility, or insufficiently collected data returns the task to the operator. Consequently, a repeatable route is not yet equivalent to a repeatable production outcome: re-surveying and manual processing may still be required after the flight.

AI primarily changes the way observations are transformed into information relevant to action. Computer vision can identify objects, surface areas, and indicators of the state of an observed asset. Economic value arises when the identified feature affects the next step: the aircraft changes the point of capture, the system directs a specialist to a suspicious area, or the operator revises the inspection plan. Without such a link, an increase in model accuracy may remain a local technical improvement. Defect recognition, for example, is useful to the customer when the result is tied to a specific asset and can be used to initiate inspection or repair. AI should therefore be evaluated across the complete decision-making chain.

The distribution of computation also changes. Responses subject to strict time constraints are appropriately executed onboard, whereas computationally intensive analysis of accumulated materials can be performed in a ground-based system. This division does not imply that every function requires continuous cloud connectivity. Rather, dependence on remote computation must be assessed against permissible latency and expected behaviour in the event of link loss. For a business, this becomes an architectural choice among the cost of onboard hardware, the availability of communications, and the complexity of maintenance. Embedding AI can therefore reduce manual labour while simultaneously increasing requirements for engineering support.

Table 1. Changes in functions during the transition to UAS with learning-based components

Function	Rule-based automation	Contribution of learning-based components	Condition for the result
Perception	Measurement and threshold signals	Recognition of objects and states	Data quality in the operating environment
Navigation	Following a predefined route	Trajectory adaptation to observations	Validation under admissible conditions
Control	Model- and controller-based response	Learning-based action strategy	Robustness and constraints
Material analysis	Transfer of data to a specialist	Identification of features and anomalies	Link to the customer's task

Source: author's analytical synthesis based on [2-4; 10]. Different modes may be combined within a single system.

Table 1 shows that the contribution of AI differs even within a single production process. Trajectory keeping is associated with control stability, object recognition with the correctness of interpretation, and mission planning with the quality of target and resource selection. Success in one component does not compensate for failure in another. A practical implication is the need to define the boundaries of algorithmic responsibility: what the algorithm decides independently, which constraints are checked separately, and when a task is handed over to a human. This distinction helps separate economically justified delegation of a function from added system complexity

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that produces no measurable improvement in the service.

What Experimental Studies Demonstrate

An important feature of the work by Loquercio et al. is the transition from sequential processing of several subtasks to a learned transformation of sensor observations into trajectories. The authors associate the result with lower processing latency and robustness to incomplete perception [3]. The economic meaning of this change should be interpreted through an expansion of the class of feasible missions: some tasks in complex environments become technically more accessible. However, the duration of autonomous flight in an experiment does not determine the aircraft's annual utilisation, the cost of preparing a site, or the need for personnel to be present. A technical advantage creates the possibility of a new service offering; demand and the organisation of execution determine whether that possibility will be used.

In the Swift experiment, the system defeated three professional pilots in 5 of 9, 4 of 7, and 6 of 9 head-to-head races, respectively [4]. Figure 1 converts the original counts into win shares. Across the full set, the result is 15 wins in 25 races, or 60%. This normalisation makes comparison transparent despite the different numbers of starts. At the same time, the indicator measures success in a specific racing task in which the outcome is determined by completion time and competition rules. It cannot be used as an estimate of delivery reliability, the quality of field processing, or flight safety over populated areas.

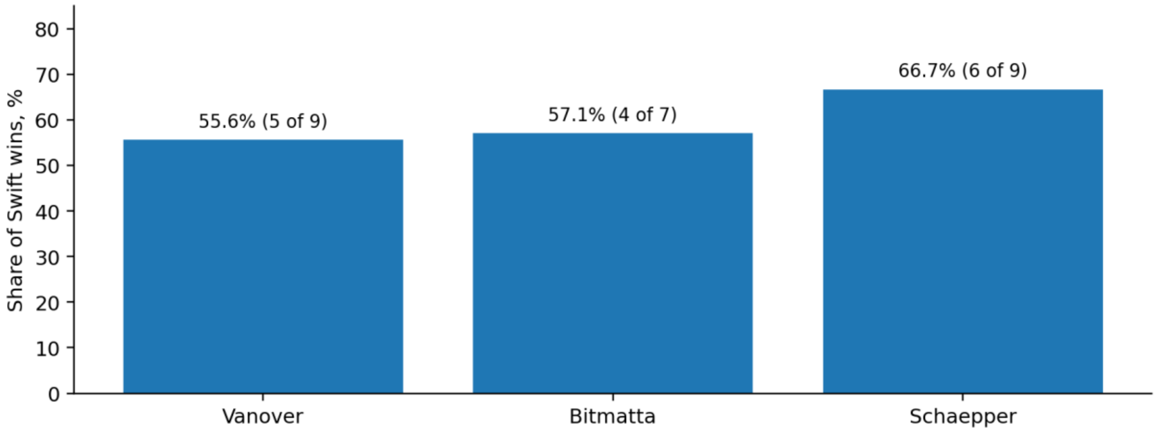

Figure 1. Results of Swift head-to-head races. Win shares calculated from the number of wins and starts reported in [4, pp. 984-985].

The substantive result of comparing the two studies lies in the changing role of software. Software increasingly implements dynamic and adaptive aircraft capabilities that were previously difficult to use autonomously. At the industry level, this creates a new field of specialisation: value is generated not only by airframe manufacturers but also by developers of perception, planning, and control systems. At the same time, the need for independent testing of software versions increases. If an update changes aircraft behaviour, the purchaser of the service should be able to establish which configuration was used and on what basis it was considered suitable for the task.

Thus, the technical literature supports the proposition that AI expands UAS capabilities. A stronger claim - that this expansion automatically translates into industry growth - requires a different body of evidence. Between a system record and a sustainable service lie preparation, operation, result processing, maintenance, and interaction with the customer. Any of these stages can become a constraint. The source of economic effect therefore lies in changes to the complete production process, while its magnitude depends on which operations are genuinely released from previous constraints.

Economic Mechanisms of AI Impact

The first mechanism concerns the reallocation of human labour. Autonomous execution of some actions can reduce the time spent on direct control and manual review of materials. However, released working time becomes a reduction in unit cost only when the organisation changes the allocation of tasks. If a specialist continues to monitor one aircraft continuously while performing the same volume of supporting work, technical autonomy alone does not increase the number of orders that can be served. Analysis therefore requires time measurement for the entire mission: preparation, transportation, deployment, execution, quality control, and delivery of the final result.

The second mechanism is improved reproducibility. In service delivery, not only the average result matters, but also the dispersion of completion

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times and quality. Re-surveying because an area was missed creates the cost of another site visit; incorrect classification requires additional verification; incomplete metadata delay acceptance. AI can reduce these losses if quality control is incorporated sufficiently early in the process. For example, detecting inadequate coverage during an inspection makes it possible to collect additional material before work at the site is completed. Value is created here by preventing a repeated cycle rather than by increasing maximum flight speed.

The third mechanism is the expansion of the range of billable services. A standalone image and interpreted information have different characteristics from the customer's perspective. In the latter case, the provider assumes part of the analytical work by linking the observation to an asset, identifying an anomaly, and presenting the result in a usable format. This creates the possibility of moving from one-off imaging to regular monitoring. Deeper processing, however, also creates obligations regarding the accuracy and explainability of results. A recognition error may trigger unnecessary work or cause a significant event to be missed; the commercial offer should therefore specify acceptable error levels and a procedure for reviewing disputed cases.

The fourth mechanism concerns the utilisation of production capacity. Forecasting task duration, maintenance requirements, and workload can help coordinate the aircraft fleet with ground resources. Yet an increase in the number of aircraft does not guarantee higher output if the constraint lies elsewhere. For analytical purposes, let demand for completed tasks be denoted by D, available technical capacity by K_t, personnel capacity by K_p, and the throughput of procedures and infrastructure by K_i. The achievable service volume Y is then constrained by $Y \le \min(D, K_t, K_p, K_i)$. This is not an estimated production function; it is a way of identifying the binding constraint.

An important implication follows from this relationship: increasing K_t through more advanced AI does not change Y if demand or ground support remains the minimum term. For example, shorter flight time will not increase daily output when most of the working day is spent travelling between customers. Likewise, faster image recognition will not deliver its full effect if acceptance of the result requires lengthy manual coordination. An investment decision should therefore begin by identifying the loss of time or quality that the investment is intended to eliminate. The maximum level of autonomy is not an independent economic objective.

Complementary investment is particularly important. The work of Brynjolfsson et al. explains why returns to AI are linked to intangible assets and may appear with a delay [13]. For UAS, such assets include accumulated mission histories, agreed quality rules, trained specialists, and integrations with customer systems. Evaluation of a specific project should distinguish one-off implementation effort from recurring operating expenditure. Otherwise, comparing the first year of adoption with a mature conventional process will conflate the effect of the technology with the effect of incomplete implementation.

The condition for economic effectiveness can be expressed through the cost of an accepted result. Suppose that, over a period, N attempts are made to provide a comparable service, the share of accepted results is p, fixed costs are F, and the average variable cost per attempt is v. For $N > 0$ and $p > 0$, the average cost per accepted result is $c = (F + vN)/(pN) = F/(pN) + v/p$. Variable costs include labour, consumables, processing, and control; a repeated attempt is included in N but does not create a second accepted service. This definition prevents an increase in the number of flights caused by rework from being incorrectly interpreted as productivity growth.

For the baseline process and the AI-enabled process, let the corresponding parameters be indexed by 0 and 1. With the same number of attempts, adoption reduces average cost if $F_1/p_1 - F_0/p_0 < N(v_0/p_0 - v_1/p_1)$. If the left-hand side is positive and the expression in parentheses on the right-hand side is also positive, there is a utilisation threshold $N^* = (F_1/p_1 - F_0/p_0)/(v_0/p_0 - v_1/p_1)$, above which additional fixed costs are offset by savings per accepted result. If there is no saving in variable cost, a higher level of utilisation alone does not ensure recovery of the additional fixed investment. This is an analytical implication of the assumptions rather than an estimate of a threshold for a particular enterprise.

The meaning of the relationship is that AI can simultaneously increase F, reduce v, and change p. Model preparation and integration increase the fixed component; automation of analysis reduces the variable component; and recognition errors affect acceptance of the result. For monitoring, p is determined by the completeness and usability of the material; for delivery, by fulfilment of the agreed obligation. Comparison is valid only at the same required level of quality: lower cost achieved by weakening acceptance criteria is not an effect of AI. The model does not assess safety and does not replace it with a monetary indicator. It explains why economic returns can differ even among operators using the same aircraft and algorithms.

Table 2. Economic content of AI applications in unmanned services

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Service	AI task	Customer outcome	Constraint on the effect
Agricultural monitoring	Identification of heterogeneous areas	Basis for inspection and decision-making	Agronomic interpretation
Inspection	Detection of signs of defects	Localised anomaly	Errors and verification cost
Mapping	Object classification	Usable data layer	Accuracy and interoperability
Delivery	Planning support	Order fulfilled within the required time	Demand and ground operations

Source: author's functional typology. Application areas are discussed with reference to [7; 10]; no measured sectoral effects are claimed.

Table 2 makes it possible to compare application areas according to the source of utility for the customer. In agriculture, timeliness and spatial accuracy may be most important; in inspection, the ability to detect and localise an anomaly; in delivery, the reproducibility of timing and the handover procedure. A universal indicator such as 'flights per aircraft' is therefore insufficient for cross-sector comparison. The number of flights may increase because of repeated work, while the duration of a single flight may fall at the expense of survey completeness. Evaluation should focus on accepted results subject to specified quality requirements and the costs incurred to obtain them.

From the Aircraft Market to the Low-Altitude Economy

In this article, the low-altitude economy is understood as the set of economic relationships surrounding civil activity in the lower layers of airspace, including production, operation, maintenance, infrastructure, and data use. The unmanned segment is the subject of analysis, but it does not exhaust all possible forms of such activity. The concept is also not reduced to a single altitude boundary: the organisational relationships examined here remain relevant despite differences in national classifications of airspace. The economic content is determined by the interconnection of services and participants, not merely by the aircraft's position above the ground.

Transition to industry scale implies a deepening division of labour. The manufacturer supplies the platform; the operator organises execution; the analytics developer processes observations; the service organisation maintains equipment readiness; and the customer uses the result within its own process. Such specialisation is justified when interactions between these links become repeatable. If every new order requires formats, evidence of quality, and methods of data transfer to be renegotiated from scratch, coordination costs rise with the market. Beyond a certain level of complexity, they may absorb the gains from automating the flight itself.

Ecosystem theory explains why technological modularity must be accompanied by coordination of complementary activities [12]. For UAS, it is useful to distinguish hardware interoperability, data interoperability, and procedural interoperability. The first enables physical or software connection among components; the second provides a common interpretation of transmitted information; and the third establishes a coordinated sequence of responsibilities and decisions. The existence of an API addresses only part of the problem. If one system considers a mission complete upon landing and another only after acceptance of the result, the same status label does not carry the same economic meaning.

A shared digital environment reduces the need to re-establish these correspondences repeatedly. In the interpretation proposed here, it includes identifiers for participants and objects, information about task conditions, an operational history, and access rules. This enables data reuse and the replacement of a supplier of an individual component without complete redesign of the process. The economic effect should be sought in shorter connection times, fewer manual reconciliations, and lower switching costs between services. This interpretation gives measurable content to the concept of an ecosystem: the quality of interaction among independent participants is evaluated rather than the number of functions in a single software product.

International Approaches to Digital Coordination

The US UTM ConOps 2.0 concept describes cooperative management of unmanned operations through distributed information exchange among operators, service suppliers, and the FAA. The document provides for a federated organisation of interoperable services; coordination relies on information about flight intent and airspace constraints [7]. The European U-space framework provides for designated zones, certified service providers, and mandatory services for flight authorisation, geo-

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awareness, network identification, and traffic information. Responsibility for the safety of the operation remains with the operator [8]. The comparison concerns the architectural principles of the documents rather than the actual economic performance of the US and EU markets.

Table 3. Comparison of digital-coordination principles

Criterion	US UTM ConOps 2.0	EU U-space
Source status	Concept of operations	Official description of the regulatory model
Organisation	Network of interacting providers	Certified providers in designated zones
Shared information	Exchange of intentions and constraints	Common information services
Operator participation	Coordination and management of own operation	Use of required services and responsibility for the operation

Source: compiled from [7; 8]. The comparison concerns functions and roles, not the degree of implementation or profitability.

A common feature of the approaches compared is that some conditions for conducting an operation are moved beyond the individual aircraft. The onboard system perceives the immediate environment, but the participant also requires information about permitted actions and the activities of other airspace users. This creates a distinction between local autonomy and overall coordination. Economically, infrastructure provides multiple participants with reusable information that would be costly or incomplete if prepared separately. Digital coordination, however, does not eliminate the operating constraints of a specific aircraft.

The distinction between a concept and a regulatory model is important when transferring international experience. An architectural description does not imply that every mechanism mentioned is already implemented everywhere or has demonstrated a positive return. For Uzbekistan, it is more useful to compare the tasks that must be solved: who keeps common information up to date, how a provider connects to the system, how identity is verified, and who is responsible for an incorrect decision. This functional approach makes it possible to adopt principles of interaction while taking local demand and infrastructure into account, rather than copying an entire organisational structure.

Remote identification illustrates the need to distinguish functions. The FAA describes Remote ID as the transmission of identification and positional information about a drone [11]. Within an economic architecture, such information can support traceability, but it does not replace navigation, authorisation of an operation, or confirmation of the quality of a delivered service. A separate data structure is needed to link these events. The order, the flight, and the accepted result must be associated with one another; otherwise, a technical log cannot establish which obligation to the customer was fulfilled.

The Dual Role of AI in the Digital Ecosystem

As the number of operations increases, AI acquires a second field of application: decision support at the level of the shared environment. Here, the object of analysis becomes the allocation of tasks, resources, and states across multiple participants. Possible applications include workload forecasting, detection of unusual events, and assessment of the quality of incoming data. These functions differ from the control of an individual aircraft in both time scale and responsibility. A demand forecast may be updated periodically, whereas information that affects whether a current action is permissible requires defined timeliness and a verification procedure.

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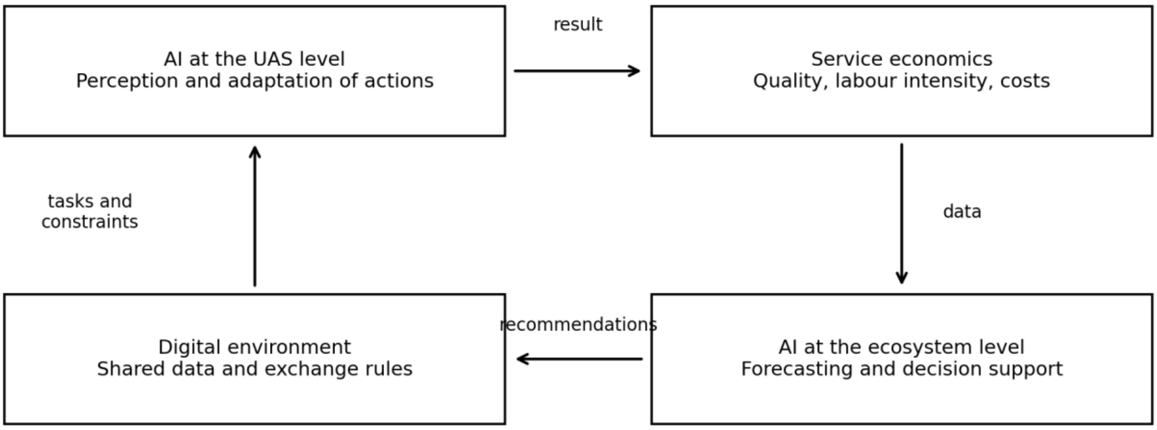

Figure 2. Relationship between AI at the UAS level and the digital ecosystem. Author's diagram; arrows indicate functional links.

Figure 2 illustrates the proposed relationship between the two levels. Onboard AI affects the feasibility and quality of actions; operational results generate data for process evaluation; and the shared digital environment enables their coordinated use. The reverse direction involves transmitting verified constraints and tasks to service providers. This relationship does not imply automatic learning of the system after every new flight. Model updates require suitable data, quality control, and validation of the new version. The number of accumulated records is useful only to the extent that they reflect conditions and outcomes that are relevant to the task being solved.

Scaling creates both benefits and new costs. Data reuse can reduce preparation costs, but a larger number of participants increases the complexity of access coordination and error correction. A shared model may detect patterns that are unavailable to a single operator, yet an error in a common service can affect several processes at once. Scientifically grounded ecosystem development therefore requires predictive functions to be combined with verifiable constraints. The principle of human-centred and safe AI application is reflected in the EASA roadmap [9]; for the architecture considered here, this implies the need to define procedures for oversight and intervention by a responsible person.

The distribution of the value created also requires attention. The data collector, model developer, and end user may be different parties. If access to operational history depends entirely on a single provider, the operator incurs switching costs when moving to another service. It is therefore appropriate to assess data portability, preservation of identifiers, and reproducibility of processing results. This matters for competition: an independent analytics company can improve an individual component of the service when connection conditions and rules for data use are defined in advance. Access, however, must remain consistent with the purpose of the information and the contractual basis for its use.

DISCUSSION: SCALING CONSTRAINTS AND IMPLICATIONS FOR UZBEKISTAN

Comparison of the technical and economic results shows that autonomy changes the frontier of feasible production, but realised output is determined by a combination of resources. This is the distinction between technological potential and economic growth. A UAS may perform a complex mission without continuous manual control yet remain underutilised because of seasonal demand or lengthy ground preparation. Conversely, a moderate improvement in data processing can substantially change the service if report preparation is the stage that delays order fulfilment. The economic significance of AI therefore depends on the position of the improved function within the production process.

The non-linearity identified by Yin et al. in regional data from China [5] is consistent with this explanation, although it does not prove it at the level of an individual enterprise. As technical capacity accumulates, the constraint may shift to data, specialists, or the organisation of demand. Additional investment in one component then yields lower returns. The regional relationship also does not establish a universal point beyond which AI becomes ineffective. It

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characterises the regions studied and the indicator used, whereas the accepted-service model provides a possible microeconomic mechanism for heterogeneous outcomes.

Agricultural monitoring clearly demonstrates the importance of the complete cycle. The customer first formulates a task for a particular field plot and time period; the operator then collects observations; an analytical service identifies anomalies; and a specialist interprets them in light of farm conditions. Utility arises when the result is incorporated into a production decision in a timely manner. High recognition accuracy does not eliminate losses if the plot is identified incorrectly, materials arrive after the relevant deadline, or indicators are not comparable with previous observations. Field identifiers, capture time, processing parameters, and acceptance criteria therefore have economic significance alongside model quality. In this setting, digital interoperability directly affects the possibility of providing a recurring service.

For Uzbekistan, this structure links sectoral AI application with the development of data and competencies envisaged by the strategic document [1]. Production specialisation emerges at the intersection of aerial operations, analytics, and sector-specific knowledge. An operator does not need to perform all of these functions independently if the output of one participant is usable at the next stage. This creates an organisational opportunity for a small aerial-imaging provider, a specialised analytics company, and a large customer to create a service jointly. Its sustainability depends on accessible interfaces, responsibility for quality, and the allocation of costs rather than on all components being owned by a single organisation.

International comparison also reveals the limits of digital centralisation. Shared infrastructure reduces duplication of information and facilitates connection, but concentrating access to operational history in a single provider increases participants' dependence. This creates an economic trade-off between the benefits of shared data and the costs of switching services. Portability of records, documented interfaces, and preservation of object identity reduce such costs. Interoperability does not, however, imply unrestricted disclosure of data: a specific interaction requires only an agreed set of information with a defined purpose and conditions of access.

The limitations of the conclusions arise from the absence of an original sample of operational data and the purposive nature of the review. Racing experiments confirm specific technical capabilities, regional econometrics characterises an aggregate relationship, and UTM and U-space describe the organisation of coordination. These sources do not provide a general estimate of the increase in value added attributable to AI and do not establish the return on its adoption in Uzbekistan. The result of the study is therefore an explanation of the links among autonomy, service costs, and interoperability among participants rather than a numerical estimate of the national market.

CONCLUSIONS AND RECOMMENDATIONS

AI contributes to the evolution of UAS by transforming observations into decisions and adapting actions to task conditions. Comparison of studies on autonomous navigation and racing control shows an expansion of technically achievable operating modes. At the same time, autonomy remains a property of the system as a whole: learning-based components complement hardware, conventional control, and operating constraints. AI is therefore one of the key technological factors of the low-altitude economy, operating together with infrastructure, energy capabilities, demand, and organisational conditions.

The economic effect operates through four mechanisms: changes in labour intensity, reductions in repeated work, expansion of the service mix, and improved resource utilisation. The analytical decomposition of the cost per accepted result shows why a reduction in manual work may coexist with higher initial costs and why utilisation affects the return on adoption. Autonomy increases output when it removes the actual binding constraint in the process; improving capacity that is already non-binding does not produce the same result.

A transition to a digital ecosystem occurs when independent participants can regularly use one another's outputs and services. Comparison of UTM and U-space reveals the common role of coordinated information, allocation of functions, and preservation of operator responsibility. On this basis, AI acquires a second field of application: analysis of the aggregate set of operations and support for coordination. A feedback loop emerges: intelligent UAS generate data and demand for a shared environment, while an interoperable environment expands the possibilities for providing unmanned services.

For Uzbekistan's digital development, an important implication is the complementarity of investment in aircraft, data, specialists, and service organisation. The unit of economic output is a completed service of agreed quality, while a sign of ecosystem development is reproducible interaction among independent providers. This approach links the technological evolution of unmanned aviation to the formation of a sustainable market without reducing the

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