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STRATEGIC DECISION DRIVERS IN KNOWLEDGE-INTENSIVE SERVICES: A DATA-DRIVEN BEHAVIORAL MODEL

Astelio Silvera Sarmiento[1]*, Moisés David Hernández Ruiz[2], Hugo Hernández Palma[3], Lesvia del Carmen Valero Barrera[4], Neila Mantilla Barbosa[5]

[1]Fundacion Universitaria para la Investigacion, el desarrollo, tecnológico y la Innovacion – IDITEK, Colombia.
[1]Fundación para la Investigación, el Desarrollo, la Innovación y la Educación Superior – Fundación IDIES, el salvador. Email: astelio@iditek.edu.co; silvera.astelio@gmail.com,
ORCID iD: https://orcid.org/0000-0001-9416-0264
[2]Corporación Universitaria del Caribe (CECAR). Email: ing.mheruiz@gmail.com,
ORCID iD: https://orcid.org/0000-0002-7651-2673
[3]Facultad de Ciencias Económicas, Universidad del Atlántico, Colombia.
Email: Hugohernandezp@mail.uniatlantico.edu.co, ORCID iD: https://orcid.org/0000-0002-3873-0530
[4]Corporación Universitaria Latinoamericana - CUL, Colombia. Email: lvalero@ul.edu.co,
ORCID iD: https://orcid.org/0000-0002-0535-0566
[5]Universidad de la Costa, CUC, Colombia. Email: nmantill3@cuc.edu.co
ORCID iD: https://orcid.org/0000-0002-0245-6613

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Corresponding Author: Astelio Silvera Sarmiento (astelio@iditek.edu.co)

ABSTRACT

This study examines the structural determinants of investment decisions in knowledge-intensive services by integrating strategic management, knowledge economy, and consumer behavior perspectives. A functional model labeled DIK (Decision to Invest in Knowledge-Intensive Services) is proposed, structured around four variables: Professional Motivation (perceived employability and projected ROI), Expected Time Return, Perceived Technological Orientation, and Optimal Duration. Using a quantitative explanatory approach and cross-sectional design, binary logistic regression was applied to estimate the marginal effects of each variable on investment intention. The model achieved a Nagelkerke R^2 of 0.64 and a correct classification rate of 78.3%, indicating strong explanatory power. Findings reveal that perceived employability (OR = 2.32) and technological orientation (OR = 2.21) are the dominant decision drivers, while time return acts as a moderating factor and excessive duration significantly reduces investment probability (OR = 0.51). The study concludes that in digitalized economies, investment decisions in knowledge-intensive services are primarily driven by expectations of future professional mobility and technological sophistication, providing strategic implications for portfolio design in knowledge-based industries.

KEYWORDS: Knowledge-Intensive Services, Perceived Employability, Technological Orientation, Investment Decision, Strategic Management, Knowledge Economy.

1. INTRODUCTION

In contemporary knowledge-based economies, intellectual capital-intensive services—such as advanced education, technology training, specialized consulting, and digital professional services—have become strategic drivers of competitiveness. Unlike traditional goods, these services are not acquired for immediate consumption, but for their potential to transform skills, generate professional mobility and improve positioning in dynamic labor markets. However, there is still limited empirical evidence that explains precisely what are the structural determinants that shape the decision to invest in this type of service.

The literature on strategic management, knowledge economics, and consumer behavior has highlighted the importance of human capital, dynamic capabilities, and digital transformation as central factors in knowledge-intensive industries. However, a gap persists between these theoretical foundations and the empirical modelling of decisional behaviour of the strategic consumer. This article addresses this gap by proposing a behavioral-explanatory model that integrates variables of perceived employability, time return, technological orientation and optimal duration within a functional architecture called the DIK model (Investment Decision in Knowledge-Intensive Services).

The central thesis argues that investment decisions in knowledge-intensive services are dominated by perceived employability and technological orientation, while time return and duration act as modulating or inhibiting variables. To test this hypothesis, a quantitative explanatory study with a cross-sectional design was developed, applying logistic regression on composite indices derived from Likert scales. The model achieved a Nagelkerke R^2 of 0.64 and a correct classification rate of 78.3%, evidencing robust explanatory capacity.

The results show that professional motivation — operationalized as perceived employability— is the strongest predictor of the investment decision (OR = 2.32), closely followed by technological orientation (OR = 2.21). Temporary return has a moderate positive effect, while excessive duration significantly reduces the probability of decision (OR = 0.51). Likewise, strategic simulations show a synergistic effect when projected employability and technological intensity are combined.

Overall, the study provides a replicable model for the strategic design of portfolios in knowledge-based industries, integrating decision-making behavior and strategic management under a data-driven approach. In this way, it contributes to understanding how consumers evaluate value in environments characterized by high intangibility, continuous innovation and accelerated digital transformation.

2. INTEGRATED THEORETICAL FRAMEWORK

Perceived Employability as a Strategic Determinant in Knowledge-Intensive Services.

Human capital theory states that knowledge-intensive education and services are investments aimed at increasing productivity and future income (Becker, 1964). This logic was expanded by Mincer (1974), who showed that future salary expectations have a direct impact on training and professional investment decisions.

Within the framework of the knowledge economy, knowledge-intensive services (KIS) are characterized by their ability to transfer specialized expertise and generate innovation (Miles, 2005; Muller & Zenker, 2001). These services act as knowledge intermediaries within innovation systems (Kox & Rubalcaba, 2007; Doloreux & Shearmur, 2012).

From a strategic perspective, competitive advantage in knowledge-based industries depends on intangible resources and dynamic capabilities (Teece, Pisano & Shuen, 1997; Teece, 2007). This logic is transferred to the strategic consumer: the investment decision is based on the expectation of acquiring skills that can be transferred to the labor market.

Perceived employability can be understood as a behavioral extension of the resource-based approach (Barney, 1991), where the individual invests in services that strengthen his or her strategic capital. Future value signaling is connected to signal theory (Spence, 1973), according to which certain attributes—such as technological accreditation or advanced specialization—function as indicators of future productivity.

The literature on innovation in KIS highlights that these services generate positive externalities on regional human capital (Strambach, 2008; Hertog, 2000). Likewise, co-creation with clients increases knowledge transfer and improves the perception of professional impact (Den Hertog, 2010; Bettencourt et al., 2002).

From behavioral economics, the expectation of professional mobility reduces the perception of risk (Kahneman & Tversky, 1979). When perceived employability is high, the decision-maker interprets the investment as an opportunity and not as an expense.

In addition, recent studies in knowledge-intensive industries show that professional development

orientation is the main predictor of purchase intent in advanced services (Alvesson, 2004; Løwendahl, 2005).

In summary, perceived employability emerges as a structural variable that integrates human capital, strategic signaling, and expectation of future return.

Temporal Return And Intertemporal Rationality In Investment Decisions

Decisions in KIS involve an intertemporal logic. The theory of rational choice under time discount explains that individuals weigh future benefits according to recovery horizon (Samuelson, 1937; Frederick, Loewenstein & O'Donoghue, 2002).

Time return is linked to the concept of educational and professional ROI (Oreopoulos & Petronijevic, 2013), where the time to capture benefits directly influences the investment decision.

From strategic management, organizational agility becomes a competitive advantage in dynamic environments (Eisenhardt & Martin, 2000). At KIS, the speed with which the service generates professional impact increases its strategic attractiveness.

The processes in KIS are emergent and difficult to standardize (Newell et al., 2009; Von Nordenflycht, 2010), which introduces temporal uncertainty. This uncertainty increases the perceived cost of time invested.

The tension between personalization and standardization also affects temporal return (Lampel & Mintzberg, 1996; Gilmore & Pine, 1997). Highly personalized services can generate greater impact, but they imply a longer duration; Standardized services reduce time but can decrease differentiation.

The theory of dynamic capabilities highlights that the rapid reconfiguration of resources allows value to be captured in less time (Teece, 2007). From the perspective of the strategic consumer, the optimal duration of service becomes a critical decisional variable.

In addition, research in behavioral economics shows that individuals exhibit hyperbolic discounting biases, preferring more immediate benefits (Laibson, 1997). This explains the preference for services with visible returns in the short term.

Therefore, the temporary return is not only a financial variable, but also a behavioral component that moderates investment intention.

Technological orientation as a sign of future competitiveness

Digital transformation has redefined knowledge-intensive services. Technological adoption is associated with innovation and competitive advantage (Porter & Heppelmann, 2014; Bharadwaj et al., 2013).

The integration of Big Data Analytics and Knowledge Management improves the quality of strategic decisions (Wamba et al., 2017; Shuradze & Wagner, 2016). At KIS, this integration becomes an indicator of sophistication.

The Task-Technology Fit approach (Goodhue & Thompson, 1995) holds that alignment between technology and tasks increases performance. From the decision-maker's perspective, this alignment increases the perception of future employability.

Studies on digital transformation show that technological orientation increases organizational resilience and adaptability (Vial, 2019; Warner & Wäger, 2019).

Likewise, the platform-based economy has transformed business models into professional services (Parker, Van Alstyne, & Choudary, 2016). Services with strong technological integration are perceived as more scalable and competitive.

Within the framework of regional innovation systems, the technological intensity of services drives economic development (Cooke, 2001; Asheim & Coenen, 2005). This reinforces the perception of strategic value.

From institutional theory, technological adoption also responds to mimetic and normative pressures (DiMaggio & Powell, 1983). Technologically advanced services generate legitimacy in the market.

Finally, the literature on organizational complexity argues that KIs operate as complex adaptive systems (Stacey, 1996; Holland, 1992), where technology acts as a facilitator of continuous learning.

Consequently, technological orientation functions as a strategic signal that reduces uncertainty, increases legitimacy and strengthens expectations of future employability.

3. METHODOLOGICAL DESIGN

The study adopted a quantitative approach of an explanatory nature, with a non-experimental design and cross-sectional, aimed at evaluating the determinants of the decision to invest in knowledge-intensive services.

The dependent variable was the Investment Decision (DIK), and the independent variables included Professional Motivation (PM), Temporary Return (RT), Technological Orientation (OT) and Optimal Duration (OD), structured under the functional model:

$$DIK = f(MP + RT + OT - DO)$$

The information was collected through a structured questionnaire with five-point Likert scales. The constructs were operationalized as normalized composite indices, verifying internal consistency using Cronbach's alpha ($\alpha > 0.78$).

The statistical analysis was developed in three stages: (1) data purification and standardization; (2) dimensional validation through exploratory factor analysis; (3) estimation of the model by binary logistic regression, suitable for a dichotomous dependent variable.

The global fit was evaluated with Nagelkerke's R^2 and Chi-square test, and β coefficients and Odds Ratios were estimated to determine the marginal impact of each variable. Parametric simulations and segmentation by clustering were also carried out to identify decisional profiles.

The model achieved adequate explanatory capacity ($R^2 = 0.64$) and a correct classification of 78.3%, confirming its relevance to test the central hypothesis.

The model is built from the analysis of perception and decision data in knowledge-intensive services, using: Weighted frequency analysis, Correlation between decisional variables, Normalization of Likert scales, Construction of composite indices

Internal validation was applied through statistical consistency and analysis of the marginal impact of each variable on investment intention.

4. PROPOSED MODEL

Empirical validation of the DIK model

To evaluate the central hypothesis—according to which investment decisions in knowledge-intensive services are dominated by perceived employability, time return, and technological orientation—the functional model was operationalized:

$$DIK = f(MP + RT + OT - DO)$$

Where:

DIK = Investment Decision in Knowledge-Intensive Services

MP = Professional Motivation (ROI, employability, professional project)

RT = Expected Temporary Return

OT = Perceived Technological Orientation

OD = Optimal Duration (if it exceeds tolerance threshold it reduces probability)

Variable	*Behavioral dimension*	*Empirical indicator*
Motivation	Expected ROI, Labor Mobility	Perceived employability index
Temporary return	Time to generate revenue	Recovery horizon
Modality	Operational flexibility	Hybrid/Digital Preference
Technology orientation	Digital service intensity	Assessment of technological tools

The variables were constructed as normalized composite indices (0–1) from Likert scales and categorical questions transformed by Z-standardization. Exploratory factor analysis was applied to verify dimensional consistency and Cronbach's alpha was calculated for each construct ($\alpha > 0.78$ in all cases), which confirmed internal reliability.

Subsequently, binary logistic regression was used, since the dependent variable (Investment Decision – DIK) was coded in terms of high vs. low investment intention.

The overall fit of the model was as follows:

Nagelkerke's $R^2 = 0.64$

Chi-square of the model: significant ($p < 0.001$)

Correct Rating: 78.3%

These indicators show that the model explains a substantial proportion of the variance in the investment decision, validating its structural relevance.

Explanatory contribution of each variable.

Below are the coefficients estimated from the logistic regression, which represent the marginal impact of each independent variable on the probability of investment. The coefficients β indicate the direction and intensity of the effect; the Odds Ratio (OR) allows us to interpret the change in relative probability in the face of a unit variation in the variable.

Professional Motivation (PM)

Coefficient $\beta = 0.84$

OR = 2.32

$p < 0.001$

Professional Motivation, built from the index of perceived employability and expectation of professional ROI, emerges as the strongest predictor of the model. An increase of one standardized unit in MP increases the relative probability of investment by 132%.

This result confirms that the decision is structurally anchored in the expectation of future labor mobility. The variable does not act as an accessory factor, but as the decisional core of the model.

It is validated that perceived employability dominates investment behavior.

Technology Orientation (OT)

Coefficient $\beta = 0.79$

OR = 2.21
$p < 0.001$

The Technological Orientation was built from the assessment of the digital intensity of the service, use of advanced tools and perception of technological updating.

An increase in OT roughly doubles the probability of investment. The proximity of the coefficient to the MP coefficient suggests that technology is not a secondary attribute, but a strategic signal of future competitiveness. It is confirmed that technological orientation is a dominant driver in knowledge-intensive services.

Temporary Return (RT)
Coefficient $\beta = 0.41$
OR = 1.51
$p < 0.05$

RT was built based on the perception of speed of investment recovery and labor impact horizon. The effect is positive but moderate. It increases the probability by 51%, but with less intensity than MP and OT. Time does not activate the decision on its own, but it enhances motivation when it is perceived as consistent with professional expectations. RT functions as a modulating variable rather than as a primary driver.

Optimal Duration (OD)
Coefficient $\beta = -0.67$
OR = 0.51
$p < 0.01$

Duration was measured as perception of temporal excess with respect to the decision-maker's tolerance threshold. When DO exceeds the optimal threshold, the probability of reversal is reduced by approximately 49%. Excessive duration introduces cognitive friction and increases the perceived opportunity cost. It is confirmed that time, when excessive, acts as a structural inhibitor.

Explanatory hierarchy of the model

The comparative analysis of standardized coefficients allows the drivers to be ordered according to their structural impact: 1. Professional Motivation (PM), 2. Technological Orientation (OT), 3. Optimal Duration (OD), 4. Temporary Return (RT). This order empirically confirms the thesis of the article: the decision is dominated by employability and technology.

Strategic simulation and robustness of the model

With the estimated coefficients, parametric simulations were performed to evaluate sensitivity:

Scenario 1: Duration reduction by 20%
Projected increase in DIK: +12%
Scenario 2: Increased technological intensity
Projected increase in DIK: +18%
Scenario 3: Simultaneous increase in PM and OT
Projected increase in DIK: +29%

The combined effect of MP and OT is synergistic. This indicates that the optimal portfolio strategy must simultaneously reinforce projected employability and technological sophistication.

Behavioral segmentation

From cluster analysis (K-means) four profiles were identified:

ROI-driven (28%)
Tech-driven (24%)
Flexibility-driven (22%)
Career-projection driven (26%)

However, even in differentiated profiles, MP and OT maintain superior structural effects. This shows that the dominant drivers operate across segments.

The estimated coefficients are not arbitrary: they derive from the statistical operationalization of constructs theoretically grounded and validated by factor analysis and logistic regression.

The DIK model:

- It explains 64% of the variance.
- It correctly classifies 78% of cases.
- It confirms that perceived employability and technological orientation are the main determinants.
- Identifies excessive duration as a significant inhibitor.
- Locate the temporal return as an intermediate modulator.

In terms of hypothesis testing, the results empirically confirm that the decision to invest in knowledge-intensive services is dominated by variables of employability and technological orientation, with secondary effects of time horizon and duration.

5. DISCUSSION

Professional motivation and perceived employability as the decision-making core. The results show that Professional Motivation ($\beta = 0.84$; OR = 2.32; $p < 0.001$) is the most robust predictor of the model, doubling the probability of inversion when it increases by a standardized unit. This finding empirically confirms the centrality of human capital as a decision-making logic, as proposed by Becker (1964) when he conceived training as a strategic investment in future productivity.

The magnitude of the coefficient indicates that perceived employability does not operate as an accessory variable, but as a dominant motivational

structure. Consistent with Spence (1973), the investment decision is activated when the service functions as a credible signal of future job positioning. Likewise, from the dynamic capabilities approach (Teece, 2007), individuals are not only looking for technical knowledge, but also transferable skills that allow them to adapt to changing environments.

The statistical value of the OR (2.32) suggests that the perception of labor mobility reduces uncertainty and reconfigures the cost-benefit evaluation, aligning with the prospective theory of Kahneman and Tversky (1979), according to which the expectation of future gain decreases risk aversion.

Consequently, the results reinforce the central thesis: in knowledge-intensive services, the decision is anchored in the expectation of future employability rather than in traditional attributes such as price or isolated reputation.

Technological orientation as a strategic sign of competitiveness. technological orientation ($\beta = 0.79$; OR = 2.21; $p < 0.001$) has a marginal impact almost equivalent to that of professional motivation. This finding is particularly relevant, as it confirms that technology is not an instrumental complement, but a structural driver.

From the perspective of Porter and Heppelmann (2014), "smart and connected" products and services transform the bases of competition. In the context of the DIK model, technology functions as an indicator of professional updating and future employability, reinforcing the motivational construct.

Likewise, the integration between Big Data Analytics and Knowledge Management (Wamba et al., 2017) has been identified as a key factor to improve organizational decision-making quality. The fact that the OR reaches 2.21 implies that technological sophistication almost doubles the probability of investment, which empirically validates Goodhue and Thompson's (1995) Task-Technology Fit approach: when the perceived service is aligned with emerging technologies, the perception of future usefulness increases.

This result also aligns with the digital transformation described by Vial (2019), where technology redefines value expectations. In behavioral terms, technology acts as a proxy for modernity, legitimacy, and competitive updating.

Therefore, the evidence confirms that employability and technological orientation form a dominant dual axis in the decision-making structure.

Temporal return as a modulating variable. Temporary return ($\beta = 0.41$; OR = 1.51; $p < 0.05$) has a positive but moderate effect. Although it increases the probability of investment by 51%, its weight is significantly lower than that of MP and OT.

This result is consistent with the theory of time discounting (Samuelson, 1937; Frederick et al., 2002), according to which individuals value immediate benefits more than delayed benefits. However, the moderate impact indicates that time alone does not activate the decision, but modulates the intensity of the main drivers.

The intertemporal logic proposed by Oreopoulos and Petronijevic (2013) holds that educational ROI depends on the recovery horizon, but the model's data suggest that, in knowledge-intensive services, return is relevant as long as it is articulated with employability and technology expectations.

From the perspective of strategic management, Eisenhardt and Martin (2000) argue that agility in capturing value is a competitive advantage. However, the model shows that speed is an accelerator, not the main engine.

This confirms that the temporal return fulfills a rational adjustment function, but does not dominate the decisional architecture.

Optimal durability as structural friction. The optimal duration ($\beta = -0.67$; OR = 0.51; $p < 0.01$) has a significant negative effect. When the perceived time exceeds the tolerance threshold, the probability of reversal is reduced by almost 50%.

This finding is consistent with Laibson's (1997) hyperbolic discount theory, which explains the preference for benefits closer in time. It is also linked to the tension between personalization and standardization described by Lampel and Mintzberg (1996): highly personalized services can extend duration and generate cognitive friction.

The magnitude of the OR (0.51) shows that excessive time not only reduces attractiveness, but also acts as a structural inhibitor. From the opportunity cost approach, the decision-maker internalizes the prolonged duration as a risk of delay in professional mobility.

Therefore, duration is not simply a logistical variable, but a strategic factor that can neutralize positive employability or technology effects if it exceeds the optimal threshold.

Robustness and overall coherence of the model. Nagelkerke's R^2 (0.64) and the correct classification rate (78.3%) indicate that the model has high explanatory capacity. These values are consistent with studies in strategic decision-making behavior in complex environments.

The parametric simulation showed that the simultaneous increase in Professional Motivation and Technological Orientation generates a

synergistic effect of 29%, higher than the individual sum of effects. This result suggests structural complementarity between projected human capital and technological sophistication, aligning with the logic of complex adaptive systems (Stacey, 1996; Holland, 1992).

In addition, segmentation into decisional profiles revealed that, although there are behavioral differences (ROI-driven, Tech-driven, etc.), the structural coefficients maintain transversal dominance. This indicates that the main drivers operate independently of the segment, reinforcing the theoretical robustness of the model.

Empirical evidence confirms the central hypothesis of the article. Investment decisions in knowledge-intensive services are not dominated by traditional variables such as price or isolated reputation, but by:

- Perceived employability (primary structural driver).
- Technological orientation (co-dominant structural driver).
- Temporal return (rational modulator).
- Optimal duration (structural inhibitor).

The convergence between statistical results and theoretical foundations strengthens the validity of the DIK model as an explanatory framework and strategic tool for portfolio design in knowledge-based industries.

6. CONCLUSIONS

The purpose of this study was to explain the structural determinants that shape the decision to invest in knowledge-intensive services. Based on a functional model based on professional motivation, temporal return, technological orientation and optimal duration, it was empirically demonstrated that decisional architecture is dominated by variables linked to projected employability and technological sophistication.

First, the results confirm that perceived employability constitutes the structural core of the decision. The magnitude of the estimated coefficient and its statistical significance show that individuals do not evaluate these services as immediate consumption, but as a strategic investment in human capital. This conclusion reinforces the postulates of the human capital theory and the dynamic capabilities-based approach, transferring these fundamentals from the organization to the behavior of the strategic consumer. In knowledge-intensive services, the promise of future professional mobility becomes the main driver of investment intention.

Second, the technological orientation emerges as a co-dominant driver. Technology does not operate only as a functional attribute, but as a sign of future competitiveness and professional legitimacy. The results show that the digital intensity of the service almost doubles the probability of investment, which confirms that in digitalized economies, technological updating is perceived as a guarantee of labor validity. This implies that knowledge-based service portfolios must explicitly integrate visible and strategically communicated technological components.

Thirdly, the temporal return acts as a modulating variable. Although its effect is statistically significant, its weight is lower than that of employability and technology. This suggests that decision-makers prioritize professional projection over the immediacy of the benefit, as long as the recovery horizon is not perceived as excessively prolonged. Time, therefore, does not determine the decision, but it does adjust its intensity.

Fourth, optimal duration is confirmed as a structural inhibitor when it exceeds the decision-maker's tolerance threshold. The significant negative impact demonstrates that the perception of temporary excess introduces cognitive friction and raises the opportunity cost. In strategic terms, duration must be carefully designed so as not to neutralize the positive effects of employability and technology.

In an integrated manner, the DIK model demonstrates theoretical consistency and empirical robustness. It explains a substantial proportion of the variance in the investment decision and allows the decisional drivers to be prioritized with structural clarity. The synergistic combination between professional motivation and technological orientation generates the greatest projected impact, which confirms that the decision does not respond to isolated variables, but to the interaction of human capital expectations and digital updating.

From the management perspective, the main contribution of the study lies in offering a replicable model for the strategic design of portfolios in knowledge-based industries. Organizations operating in this type of market must structure their value proposition around three central axes: impact on employability, technological intensity, and time optimization. The duration and modality must be adjusted as tactical variables to maximize the probability of investment.

Finally, the study contributes to the literature on knowledge-intensive services by integrating consumer behavior, strategic management, and knowledge economy into a behavioral-explanatory

model. Investment decisions in this type of service cannot be understood from traditional marketing or price approaches; require a structural reading oriented to projected human capital and future technological competitiveness.

In short, the central hypothesis is confirmed: in knowledge-intensive services, the investment decision is dominated by perceived employability and technological orientation, while the time return and duration operate as adjustment and inhibition variables. The proposed model offers a solid basis for future comparative research and for the development of more sophisticated predictive tools in digital economy contexts.

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