Monthly journal of
CORVINUS UNIVERSITY OF BUDAPEST

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www.vezetestudomany.hu

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**ISSN:** ISSN 0133-0179 (Print);
ISSN 3057-9376 (Online)

**PREPARATION AND PRINTING:**
CC Printing Kft. • ccprinting.hu

**SUBSCRIPTION:**

It is distributed by subscription by the Newspaper Business Unit of Magyar Posta Rt. Subscriptions can be made directly to the delivery people, at any post office in the country, at the Newspaper Customer Service Offices in Budapest and at the Central Newspaper Center (Budapest VIII., Orczy tér 1.
p: 06 1 477-6300; p.cím: Bp., 1900).
i: 06 80 444-444
e: hirlapelofizetes@posta.hu

Subscription fee for one year 20700 HUF
Price per copy: 2000 HUF

Published monthly.
Some copies can be purchasedat
the Editorial Office, Fővám tér 8.
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# VEZETÉSTUDOMÁNY

Vol. 57., Iss. 11. 2026

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A Budapesti Corvinus Egyetem szakfolyóirata
Published by the Corvinus University of Budapest

www.vezetestudomany.hu

IMAD TRIBAK – ÁRPÁD PAPP-VÁRY – ZOLTÁN SZABÓ

# TRANSPARENCY MATTERS – HOW SPONSORSHIP DISCLOSURE FORMAT SHAPES CREDIBILITY AND CONSUMER RESPONSES THROUGH PERCEIVED TRANSPARENCY IN INSTAGRAM MICRO-INFLUENCER MARKETING?

# A TRANSZPARENCIA SZÁMÍT – HOGYAN ALAKÍTJA A SZPONZORÁCIÓS KÖZZÉTÉTEL FORMÁTUMA A HITELESSÉGET ÉS A FOGYASZTÓI REAKCIÓKAT AZ ÉSZLELT TRANSZPARENCIÁN KERESZTÜL AZ INSTAGRAM MIKROINFLUENCER MARKETINGBEN?

This study examines how sponsorship disclosure format and influencer compensation nature shape perceived sponsorship transparency and its effects on source credibility, information credibility, online engagement, and purchase intention among Instagram micro-influencers. Drawing on the Persuasion Knowledge Model, Communication Transparency Theory, Parasocial Interaction Theory, and Source Credibility Theory, the study conceptualizes perceived sponsorship transparency as consumers' holistic judgment of how openly the commercial relationship is communicated. A between-subjects experiment (420 participants) was analyzed using two-way analysis of variance, regression, and serial mediation. Disclosure format, but not compensation nature, influenced perceived transparency, with platform-integrated disclosures outperforming hashtag-based ones, extending the Persuasion Knowledge Model to platform-governed ecosystems. Transparency sequentially mediated behavioral outcomes through source and information credibility, with source credibility the stronger mediator. Limitations include snowball sampling, a fictitious influencer and brand, and no confirmatory factor analysis.

Keywords: **sponsorship disclosure format, compensation nature, perceived sponsorship transparency, credibility, online engagement, purchase intention, micro-influencer**

Ez a tanulmány azt vizsgálja, hogyan befolyásolja a szponzorációs közzététel formátuma és az influencer-kompenzáció jellege az észlelt szponzorációs transzparenciát, és annak hatásait a forrás- és információs hitelességre, az online elköteleződésre és a vásárlási szándékra az Instagram mikroinfluencerek körében. A Meggyőzési Tudás Modellre, a Kommunikációs Transzparencia Elméletre, a Paraszociális Interakció Elméletre és a Forrás Hitelesség Elméletre támaszkodva az észlelt szponzorációs transzparenciát a kereskedelmi kapcsolat nyíltságáról alkotott átfogó fogyasztói ítéletként értelmezik a szerzők. Csoportközi kísérlet (420 résztvevő) adatait kétszempontos varianciaanalízissel, regresszióval és soros mediációs elemzéssel értékelték. A közzététel formátuma, de nem a kompenzáció jellege befolyásolta az észlelt transzparenciát: a platformba integrált közzétételek erősebb transzparenciát eredményeztek, mint a hashtag-alapúak, kiterjesztve a Meggyőzési Tudás Modellt a platformvezérelt ökoszisztémákra. A transzparencia szekvenciálisan mediálta a viselkedéses kimeneteleket a forrás- és információs hitelességen keresztül, a forráshitelesség bizonyult erősebb mediátornak. Korlátok: hólabda-mintavétel, fiktív influencer és márka, valamint a konfirmatorikus faktorelemzés hiánya.

Kulcsszavak: **szponzorációs közzététel formátuma, kompenzáció jellege, észlelt szponzorációs transzparencia, hitelesség, online elköteleződés, vásárlási szándék, mikroinfluencer**

**Funding/Finanszírozás:**
The authors did not receive any grant or institutional support in relation with the preparation of the study.
A szerzők a tanulmány elkészítésével összefüggésben nem részesültek pályázati vagy intézményi támogatásban.

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The article was received: 15. 12. 2025, revised: 24. 03. 2026, 29. 03. 2026, 11. 04. 2026 and 27. 04. 2026, accepted: 11. 05. 2026.
A cikk beérkezett: 2025. 12. 15-én, javítva: 2026. 03. 24-én, 2026. 03. 29-én, 2026. 04. 11-én és 2026. 04. 27-én, elfogadva: 2026. 05. 11-én.

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Social media influencers shape purchase behavior and consumer attitudes (Zhang & Szabó, 2024), making influencer marketing one of the most effective forms of digital advertising. Over 80% of marketers consider it highly effective, and nearly 64% of brands include influencers in their 2025 media strategies (Influencer Marketing Hub, 2025). Instagram remains the primary channel, with over three billion monthly active users (Demand Sage, 2026), and the global influencer marketing industry is projected to surpass $31 billion by 2027 (Statista, 2026). However, increasing commercialization has raised concerns about credibility, authenticity, and transparency (Baghel, 2023), as even digitally fluent consumers struggle to distinguish sponsored from organic content (Evans et al., 2017; Sárközi & Szabó, 2024).

Among influencer tiers, micro-influencers (10 000–100 000 followers) occupy an intermediary role between brands and consumers, leveraging perceived authenticity, niche expertise, and relational closeness (Conde & Casais, 2023; De Cicco et al., 2021). Their content reflects personal experiences that enhance trust, engagement, and the likelihood of acting on recommendations (Aldlimi et al., 2025).

Micro-influencers often engage in hybrid compensation models combining financial and in-kind partnerships, blurring boundaries between personal endorsement and paid promotion (Lou & Yuan, 2019). Sponsorship disclosures are therefore critical, as transparency influences credibility, engagement, and purchase intention (Evans et al., 2017). Despite regulatory requirements, introduced by the FTC (2013) and EASA (2018), compliance remains low, with only about 20% of influencers fully adhering to guidelines (European Parliament, 2025), and platform tools such as Instagram's "Paid Partnership" tag are applied inconsistently (Carpenter & Bonin II, 2021).

A key gap remains in understanding how different disclosure formats influence consumer perceptions of micro-influencers. Few studies compare multiple formats (none, implicit, explicit, platform-tagged) while examining the mediating role of perceived sponsorship transparency on credibility and behavioral responses such as engagement and purchase intention. Prior research highlights a paradox: explicit disclosures increase advertising recognition but may reduce perceived trustworthiness (Boerman, 2020; Jhawar et al., 2025), posing challenges for micro-influencers whose effectiveness depends on authenticity.

Much of the disclosure literature conceptualizes transparency as advertising recognition (Wojdynski & Evans, 2016; Boerman et al., 2017). However, contemporary influencer marketing operates within platform-governed environments where disclosure is embedded in interface design (Giuffredi-Kähr et al., 2022; Cao & Belo, 2024). For Generation Y and Z, transparency is evaluated not only by recognizing advertising, but by how openly the commercial relationship is communicated (Evans et al., 2019; Wojdynski et al., 2018), as an evaluative interpretation rather than mere persuasion knowledge activation (Friestad & Wright, 1994; Van Reijmersdal et al., 2023; Eisend et al., 2020).

The present study examines how different sponsorship disclosure formats shape perceived sponsorship transparency and influence credibility and customer responses. Disclosure is conceptualized as activating cognitive evaluation processes operating through perceived sponsorship transparency rather than directly determining behavioral outcomes. Drawing on Wojdynski et al.'s (2018) multidimensional framework and Communication Transparency Theory, transparency is conceptualized as consumers' evaluation of the influencer–brand relationship, encompassing brand presence clarity, commercial arrangement visibility, and absence of deceptive intent, understood as an evaluative judgment particularly consequential for advertising-literate Generation Y and Z audiences.

This evaluative process triggers credibility judgments at two levels. Source credibility reflects transparency's influence on audience evaluations of the influencer, including trustworthiness, expertise, attractiveness, and similarity (Ohanian, 1990; Munnukka et al., 2016), dimensions especially salient where parasocial closeness heightens sensitivity to authenticity cues. Information credibility captures evaluations of the sponsored message's reliability and accuracy (Xiao et al., 2018). Together these dimensions mediate the relationship from perceived sponsorship transparency to online engagement and purchase intention. The framework integrates the Persuasion Knowledge Model as the primary theory, Parasocial Interaction Theory as relational context, Communication Transparency Theory as the mechanism through which openness is interpreted, and Source Credibility Theory as the link between transparency and credibility, with perceived sponsorship transparency as the central construct.

The study is guided by the following main research question: To what extent does perceived sponsorship transparency mediate the relationship between sponsorship disclosure format and customer responses among Instagram micro-influencers? Sub-questions examined are:

- **RQ1:** Does sponsorship disclosure format differentially influence perceived sponsorship transparency across disclosure conditions?
- **RQ2:** Does the nature of influencer compensation (financial vs. in-kind) influence perceived sponsorship transparency?
- **RQ3a:** Does perceived sponsorship transparency positively influence source credibility?
- **RQ3b:** Does perceived sponsorship transparency positively influence information credibility?
- **RQ3c:** Does perceived sponsorship transparency indirectly influence online engagement through source and information credibility?
- **RQ3d:** Does perceived sponsorship transparency indirectly influence purchase intention through source and information credibility?

The remainder of the paper proceeds as follows: the next section presents the literature review and conceptual framework, followed by the materials and methods, results, and discussion of key findings, implications, limitations, and directions for future research.

## Literature Review

### Influencers and Parasocial Relationships

Influencers are social media personalities who cultivate engaged followings in specialized fields such as fashion, lifestyle, gaming, or technology (Chen et al., 2024; Lou & Yuan, 2019; Schouten et al., 2020). Micro-influencers, typically having between 5 000 and 100 000 followers (Janssen et al., 2022), generate higher engagement and trust than macro counterparts (Conde & Casais, 2023; De Cicco et al., 2021) through niche expertise and genuine interests (Aldlimi et al., 2025).

Parasocial Interaction Theory (Horton & Wohl, 1956; Rubin et al., 1985) describes these dynamics as one-sided psychological connections resembling friendships, increasing perceived intimacy and strengthening persuasion (Schouten et al., 2020; Boerman, 2020). Followers apply interpersonal norms of honesty and sincerity when evaluating influencer behavior, interpreting communications as relational interactions rather than purely commercial messages (Balaban et al., 2022).

This relational closeness creates vulnerability; poorly disclosed sponsorships can undermine trust and heighten betrayal when economic motives remain hidden (Jin et al., 2019; Van Reijmersdal et al., 2016). Open acknowledgment of commercial intent may be interpreted as relational integrity (Audrezet et al., 2020), whereas concealed sponsorship may violate expectations associated with perceived friendship (Giuffredi-Kähr et al., 2022). The strength of parasocial bonds directly conditions message acceptance; followers perceiving high relational closeness are more likely to accept transparent disclosures as consistent with the influencer's authentic self (Breves et al., 2021), while the same followers may be disproportionately resistant when transparency is absent (Balaban et al., 2022), making commercial intent communication a decisive factor in whether sponsored content is accepted or rejected (Sheng et al., 2023).

When commercial intent is revealed clearly, it may reduce perceptions of deception and be interpreted as relational transparency rather than regulatory compliance (Karagür et al., 2022). Conversely, vague disclosures may obscure commercial intent, creating the impression that content is genuine rather than commercially motivated, thereby violating relational norms. This relational sensitivity provides the contextual foundation for understanding how disclosure formats influence perceived sponsorship transparency.

### The Persuasion Knowledge Model and Disclosure Effects

While Parasocial Interaction Theory establishes the relational context in which disclosure is evaluated, the Persuasion Knowledge Model explains the cognitive mechanism through which consumers process and respond to sponsorship cues.

The PKM (Friestad & Wright, 1994) posits that consumers activate persuasion knowledge when exposed to marketing tactics, though this does not automatically lead to resistance (Eisend & Tarrahi, 2022); responses depend on how the persuasive attempt is evaluated in terms of honesty and fairness (Lee et al., 2021; Karagür et al., 2022). In influencer marketing, disclosure triggers persuasion knowledge (Boerman et al., 2017), but whether awareness results in skepticism or acceptance depends on how transparently the commercial relationship is communicated (Eisend & Tarrahi, 2022). When perceived as open and non-deceptive, activated persuasion knowledge may generate perceptions of honesty rather than resistance (Cao & Belo, 2023), with perceived sponsorship transparency representing the evaluative stage shaping whether disclosure enhances or undermines credibility (Karagür et al., 2022).

Drawing on PKM alongside Communication Transparency Theory (Rawlins, 2008; Men et al., 2020), explicit disclosure signals relational integrity. Communication Transparency Theory identifies three core dimensions; substantive information sharing, participatory communication, and accountability, translating in the influencer context into clarity of brand identification, openness of disclosure language, and perceived absence of manipulative intent (Karagür et al., 2022), collectively shaping whether disclosures are evaluated as genuinely transparent or merely performative (De Cicco et al., 2021).

Explicit disclosures signal commercial intent while communicating openness (Boerman, 2020), whereas implicit disclosures may activate persuasion knowledge without sufficiently signaling honesty (Audrezet et al., 2020; Bu et al., 2022). Transparency perceptions may also depend on compensation nature; in-kind rewards appear more authentic, whereas monetary compensation is interpreted as more transactional (Audrezet et al., 2020; Jin et al., 2019), and when compensation arrangements are perceived as congruent with authentic self-presentation, transparency perceptions are strengthened (Breves et al., 2021; Xie & Feng, 2023). Monetary compensation may increase the importance of clear disclosure (Xie & Feng, 2023; De Cicco et al., 2021), whereas in-kind compensation may reduce reliance on explicit disclosure cues (Audrezet et al., 2020). Accordingly:

> *H1: Sponsorship disclosure format and influencer compensation nature jointly influence perceived sponsorship transparency.*
> *H1a: Sponsorship disclosure format differentially influences perceived sponsorship transparency across disclosure conditions.*
> *H1b: The nature of influencer compensation (financial vs. in-kind) influences perceived sponsorship transparency.*

Within PKM, perceived sponsorship transparency functions as the cognitive bridge between disclosure recognition and subsequent evaluations.

### From Transparency to Credibility and Customer Responses

Transparent disclosure has downstream consequences for both the influencer and the message. Source Credibility

Theory (Hovland et al., 1954; Ohanian, 1990) posits that communicator effectiveness depends on attractiveness, trustworthiness, expertise, and similarity (Munnukka et al., 2016), dimensions in which micro-influencers typically perform strongly. Integrating PKM with Source Credibility Theory, transparency serves as a diagnostic cue signaling the influencer's credibility; perceived transparency strengthens credibility evaluations by reducing suspicions of hidden motives (Boerman et al., 2017; Metzger & Flanagin, 2013), functioning as a reputational safeguard maintaining authenticity and sincerity (De Veirman & Hudders, 2020; Woodroof et al., 2020). Accordingly:

*H2: Perceived sponsorship transparency positively influences source credibility.*

Information credibility refers to the perceived reliability, accuracy, and neutrality of the sponsored message (Johnson & Kaye, 2015; Jamal et al., 2021; Ou & Ho, 2024). Transparent sponsorship leads audiences to view messages as honest and unbiased, whereas ambiguous disclosures raise suspicion and reduce confidence in message claims (Cao & Belo, 2023; Sheng et al., 2023). From a PKM perspective, openly communicated persuasive intent reduces the need for cognitive defense, translating into greater willingness to accept message content as reliable (Eisend & Tarrahi, 2022; De Cicco et al., 2021), with information credibility further emerging from social cues such as likes and peer engagement (Yin et al., 2018). Accordingly:

*H3: Perceived sponsorship transparency positively influences information credibility.*

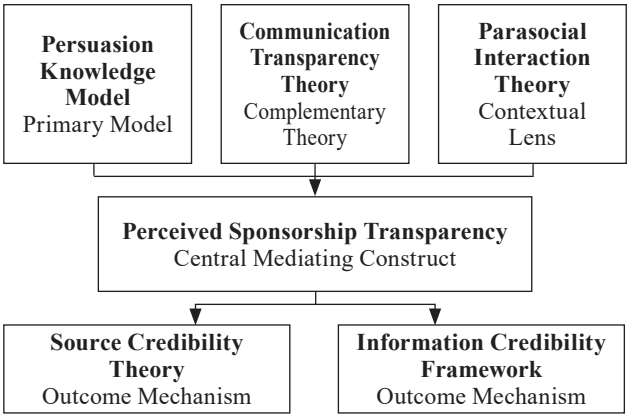
Although conceptually related, source and information credibility represent analytically distinct evaluations; audiences may perceive an influencer as trustworthy while questioning product claims, or vice versa (Van Reijmersdal et al., 2024; Liu & Zheng, 2024), and are therefore conceptualized as parallel mediating mechanisms through which perceived sponsorship transparency influences customer responses. Within the parasocial and PKM frameworks established earlier, credibility judgments shaped by transparency perceptions function as the evaluative outcomes that ultimately drive behavioral responses. Credible influencers generate stronger engagement and purchase intentions (Lou & Yuan, 2019; Martínez-López et al., 2020), and when sponsored information is perceived as accurate, message plausibility increases, enhancing willingness to interact and consider product adoption (Liu & Zheng, 2024; Han & Balabanis, 2024).

*H4a: Source credibility positively influences online engagement.*
*H4b: Source credibility positively influences purchase intention.*
*H5a: Information credibility positively influences online engagement.*
*H5b: Information credibility positively influences purchase intention.*

Figure 1 illustrates the hierarchical theoretical summary of the present study, depicting the integrative role of the four theoretical perspectives and their convergence through perceived sponsorship transparency as the central mediating construct.

Figure 1

**Hierarchical Theoretical Summary**

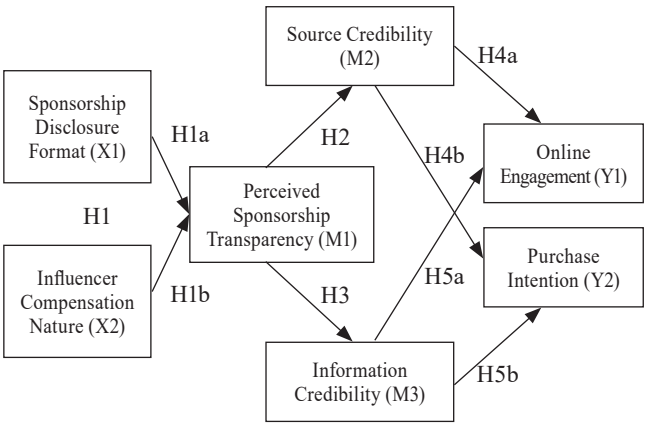



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The conceptual model (Figure 2) summarizes these relationships. Sponsorship disclosure format and compensation nature serve as independent variables influencing perceived sponsorship transparency (mediator 1). Transparency affects source (mediator 2) and information credibility (mediator 3), which drive online engagement and purchase intention (dependent variables). The framework integrates cognitive and relational processes to explain how transparency transforms disclosure practices into customer responses.

Figure 2

**Conceptual Framework**




*Source: own elaboration*

The following section details the research design, measurement scales, and data analysis techniques, followed by the results and discussion of key findings, implications, limitations, directions for future research, and conclusions.

## Method

### Research Approach and Design

To investigate how Instagram sponsorship disclosures affect perceived sponsorship transparency, a quantitative approach was used to test hypotheses and quantify relationships. The study employed a deductive, causal design to examine cause-and-effect links between sponsorship disclosure format, compensation nature, perceived sponsorship transparency, credibility, and customer responses (Hernán & Robins, 2020).

A between-subjects experimental design manipulated two independent variables: sponsorship disclosure format (none, implicit, explicit, and explicit with Instagram's "Paid Partnership" tag) and compensation nature (financial or in-kind). These manipulations created seven experimental conditions. Participants were randomly assigned, with a target of 60 respondents per condition.

### Sampling and Data Collection

Non-probability snowball sampling was used via an online questionnaire distributed on social media. While not fully representative, it is suitable for targeting Instagram users aged 18–39 (Generations Y and Z), the primary audience of influencer marketing.

Data were collected via Google Forms between October 2024 and April 2025. There were 420 valid responses, equally distributed across seven conditions (n = 60 per group) (Table 1).

To ensure alignment with the research objective, examining perceived sponsorship transparency among Instagram micro-influencers, several inclusion criteria were applied. Participants were required to:

1. Be between 18 and 39 years of age.
2. Possess an active Instagram account.
3. Report prior exposure to influencer content on Instagram
4. Indicate familiarity with sponsored posts or paid partnerships on the platform
5. Report familiarity with or prior exposure to micro-influencer content, defined as accounts with between 5,000 and 100,000 followers operating within niche interest areas.

Familiarity with micro-influencer content was particularly important given the study's focus on this influencer tier, ensuring participants could meaningfully evaluate sponsorship disclosure formats and transparency cues within influencer content. Responses were screened for eligibility and completeness prior to analysis, with incomplete responses or those not meeting inclusion criteria excluded before group allocation. Data collection continued until 420 valid responses were achieved, yielding equal group sizes across seven conditions (n = 60 per group) (Table 1). All participants demonstrated meaningful engagement with influencer content and met the micro-influencer familiarity criterion, confirming sample relevance. Demographic characteristics, Instagram usage patterns, and prior experience with sponsored content are reported in section 4.1.

### Experimental Stimuli and Scenario Design

Participants viewed a mock Instagram post created with Zeoob.com to simulate realistic influencer marketing setting (see Appendix 1). The stimuli featured Emma Morgan, a fictional micro-influencer, promoting Latifa, a fictional phone accessory brand. The profile, young, tech-savvy, and relatable, reflected typical micro-influencer characteristics, while the fictional brand minimized pre-existing bias.

Seven distinct posts represented each condition, varying in compensation framing and disclosure visibility: no disclosure, implicit disclosure (like "Shoutout to @Latifa!"), explicit disclosure (like "#ad" or "#sponsored"), and explicit disclosure paired with Instagram's "Paid Partnership" tag. Compensation was described as "supporting me" or "gifted product". Each post included a photo, caption, and disclosure statement mimicking Instagram's interface (Table 2).

Table 1

**Experimental Design**

| Sponsorship Disclosure Format / Compensation Nature | No Disclosure | Implicit Disclosure | Explicit Disclosure | Explicit Disclosure Combined with Instagram Tag "Paid Partnership" |
|---|---|---|---|---|
| **Financial Compensation** | – | 60 participants (random distribution) | 60 participants (random distribution) | 60 participants (random distribution) |
| **In-Kind Compensation** | – | 60 participants (random distribution) | 60 participants (random distribution) | 60 participants (random distribution) |
| **No Compensation** | 60 participants (random distribution) | – | – | – |

*Source: own elaboration*

Table 2

**Seven Experimental Groups**

| | No Disclosure | Implicit Disclosure | Explicit Disclosure | Explicit Disclosure Combined with Instagram Tool |
|---|---|---|---|---|
| **Financial Compensation** | – | Shoutout to @ Latifa! #Ad | Shoutout to @Latifa for supporting me! #Sponsored | *Paid partnership with Latifa* + Shoutout to @Latifa for supporting me! #Sponsored |
| **In-Kind Compensation** | – | Shoutout to @ Latifa! #Gifted | Shoutout to @Latifa for this complimentary! #Sponsored | *Paid partnership with Latifa* + Shoutout to @Latifa for this complimentary! #Sponsored |
| **No Compensation** | N/A | – | – | – |

*Source: own elaboration*

### Questionnaire Design

The questionnaire contained five sections. The first included screening questions verifying eligibility based on the inclusion criteria mentioned previously, followed by perceptions of the Instagram post, followed by measures of perceived sponsorship transparency, source credibility, and information credibility. Subsequent sections evaluated online engagement and purchase intention for the product. The final section collected demographics and Instagram usage patterns.

### Measurement Scales

All key constructs were measured using previously validated multi-item scales adapted for the Instagram context, employing a 7-point Likert scale (1 = Strongly Disagree, 7 = Strongly Agree).

Perceived sponsorship transparency was measured using the 12-item scale developed by Wojdynski et al. (2018), which captures brand presence, sponsorship clarity, disclosure visibility, and the perceived absence of deception. This scale was selected because it was specifically designed to measure how audiences evaluate transparency in sponsored and native advertising contexts, making it highly suitable for examining disclosure practices on Instagram ($\alpha = 0.86–0.95$).

Source credibility was measured using the scale developed by Munnukka et al. (2016), adapted from the model proposed by Ohanian (1990). The scale includes four dimensions, attractiveness, trustworthiness, expertise, and similarity, and was chosen because it specifically evaluates the credibility of peer endorsers in social media environments, which closely aligns with the role of influencers ($\alpha = 0.82–0.91$).

Information credibility was assessed using a five-item scale adapted from Xiao et al. (2018). This scale measures perceived accuracy, trustworthiness, and reliability of influencer-generated content and was selected due to its relevance to evaluating credibility within social media influencer contexts ($\alpha = 0.97$).

Online engagement was measured through six items derived from Boerman (2020), capturing behavioral and attitudinal engagement such as liking, commenting, sharing, and following the influencer. This scale was chosen because it was developed specifically to examine audience responses to disclosure practices on Instagram, aligning closely with the experimental setting of the present study ($\alpha = 0.91$).

Purchase intention was captured using a five-item scale based on Dabholkar and Sheng (2012), which evaluates respondents' likelihood of purchasing the featured product. This scale was selected because it is widely used in online consumer behavior research and reliably measures consumers' behavioral intentions in digital purchasing contexts ($\alpha = 0.90$).

Full scale items and adaptations for all constructs are provided in Appendix 2.

## Data Analysis

Data were screened for completeness and outliers before hypothesis testing. Descriptive statistics summarized demographic characteristics and key patterns. Reliability and validity were confirmed using Cronbach's alpha ($\alpha \geq 0.70$), Bartlett's test of sphericity ($p < 0.05$), and the Kaiser-Meyer-Olkin (KMO) measure (KMO > 0.70). Principal Component Factor Analysis with Varimax rotation verified discriminant validity and dimensional structure.

A two-way ANOVA assessed mean differences among the experimental groups, examining the main effects of sponsorship disclosure format and compensation nature on perceived sponsorship transparency, as well as their interaction effect. Regression analyses determined the extent to which independent variables explained variance in mediating and dependent variables. Stepwise multiple regression identified which dimensions of perceived sponsorship transparency and source credibility contributed most strongly to online engagement and purchase intention.

Hayes' PROCESS macro (Version 4.3) for SPSS examined mediation effects (Hayes, 2022). Model 6 investigated serial mediation, where relationships between sponsorship disclosure format and dependent variables were mediated by perceived sponsorship transparency (M1) source credibility (M2), and information credibility (M3), adjusting for compensation nature. Bootstrap technique used 5,000 resamples and 95% confidence intervals; indirect effects were significant when intervals excluded zero.

This analytical approach provided comprehensive analysis of direct and indirect effects by combining relational, cognitive, and communicative aspects of influencer marketing.

## Results

### Sample Characteristics

*Demographic Profile*

The final sample included 420 participants randomly assigned to seven conditions (60 per group). Respondents were 55.2% female, 39% male, and 5.7% preferred not to disclose gender. All participants were aged 18-39 (Generations Y and Z), and 85.8% held or were pursuing university degrees (Table 3).

Table 3

**Demographic Profile**

| Variable | Items | Frequency | Percentage |
|---|---|---|---|
| **Gender** | Female | 232 | 55.2% |
| | Male | 164 | 39% |
| | I prefer not to answer | 24 | 5.7% |
| **Age** | 18 - 25 | 162 | 38.6% |
| | 26 - 30 | 186 | 44.3% |
| | 31 - 35 | 48 | 11.4% |
| | 36 - 39 | 24 | 5.7% |
| **Education** | High school degree | 40 | 9.5% |
| | Vocational training | 20 | 4.8% |
| | Bachelor's degree | 130 | 31% |
| | Master's degree | 186 | 44.3% |
| | PhD | 44 | 10.5% |

*Source: own elaboration*

*Instagram Use*

83.8% of participants used Instagram daily and 16.2% weekly, with 21% identifying as influencers themselves, indicating high familiarity with influencer content. These characteristics confirm the sample represents the target audience of young, tech-savvy users (Table 4).

Table 4

**Instagram Use**

| Variable | Items | Frequency | Percentage |
|---|---|---|---|
| Do you have an Instagram account? | Yes | 420 | 100% |
| | No | 0 | 0% |
| Usage frequency | Daily | 352 | 83.8% |
| | Weekly | 68 | 16.2% |
| Do you consider yourself an influencer? | Yes | 88 | 21% |
| | No | 332 | 79% |

*Source: own elaboration*

### Reliability and Validity of the Scales

All scales demonstrated adequate reliability and validity, confirmed using Cronbach's alpha, KMO index, and Bartlett's test. Perceived sponsorship transparency retained three dimensions (brand presence, disclosure, and lack of deception) after eliminating the "sponsorship clarity" dimension due to low internal consistency ($\alpha = .522$). A second exploratory factor analysis yielded high sampling adequacy (KMO = 0.893), significant Bartlett's test ($p < .001$), substantial explained variance (87.4%), and satisfactory internal consistency ($\alpha = 0.779$–$0.888$), with all factor loadings exceeding the commonly accepted threshold, collectively providing reasonable empirical support for the coherence and validity of the retained construct. The absence of a confirmatory factor analysis (CFA) is acknowledged as a limitation of the present study.

Source credibility retained four dimensions: attractiveness, trustworthiness, expertise, and similarity (KMO = 0.872; variance = 85.7%), with one item ("The influencer looks sexy") *removed* due to cross-loading, and all factors exceeding $\alpha > .70$. Information credibility was unidimensional with five items, showing strong reliability ($\alpha = .928$) and validity (KMO = 0.926; variance = 65%). Online engagement demonstrated exceptional reliability ($\alpha = .967$), KMO = 0.939, and variance = 98.6%. Purchase intention showed strong reliability ($\alpha = .928$) and validity (KMO = 0.864; variance = 82.8%) after removing one negatively worded item "I don't believe I'd ever consider buying this product."

### Descriptive Statistics

Mean scores for perceived sponsorship transparency (M = 4.14), source credibility (M = 5.59), information credibility (M = 5.38), online engagement (M = 5.15), and purchase intention (M = 4.86) all exceeded the scale midpoint, suggesting favorable perceptions and behavioral intentions. Source credibility showed the highest mean and lowest variability (SD = 1.00), while information credibility, online engagement, and purchase intention reflected greater variability (SDs = 1.94–2.04). Explicit disclosures, particularly combined with Instagram's "Paid Partnership" tag, yielded the highest scores across constructs, while no-disclosure conditions yielded the lowest, suggesting explicit disclosures enhance credibility perceptions and customer responses (Tables 5 and 6).

Table 5

**Descriptive Statistics of the Measurement Scales**

| Scale | N | Min | Max | Mean | Std. Deviation | Variance |
|---|---|---|---|---|---|---|
| Perceived Sponsorship Transparency. | 420 | 1.00 | 6.33 | 4.1397 | 1.20789 | 1.461 |
| Source Credibility | 420 | 2.57 | 7.00 | 5.5874 | 1.00071 | 1.001 |
| Information Credibility | 420 | 1.00 | 7.00 | 5.3829 | 1.94067 | 3.766 |
| Online Engagement | 420 | 1.00 | 7.00 | 5.1508 | 1.99847 | 3.994 |
| Purchase Intent | 420 | 1.00 | 7.00 | 4.8560 | 2.03933 | 4.159 |

*Source: own elaboration*

Table 6

**Descriptive Statistics of the Measurement Scales according to the Experimental Groups**

| Scale | No disclosure | Implicit disclosure | | Explicit disclosure | | Explicit disclosure combined with Instagram tool | |
|---|---|---|---|---|---|---|---|
| | | Financial | In-kind | Financial | In-kind | Financial | In-kind |
| Perceived Sponsorship Transparency. | 2.0593 | 3.8519 | 3.1037 | 4.8185 | 4.7963 | 5.2704 | 5.0778 |
| Source Credibility | 4.8310 | 4.7976 | 4.8000 | 5.9071 | 6.1738 | 6.3476 | 6.2548 |
| Information Credibility | 3.8667 | 3.5667 | 3.8333 | 6.5200 | 6.4000 | 6.7400 | 6.7533 |
| Online Engagement | 3.6500 | 3.5167 | 3.5000 | 6.2111 | 6.3000 | 6.5733 | 6.2889 |
| Purchase Intent | 3.2000 | 3.2000 | 3.1833 | 6.1500 | 6.0000 | 6.2917 | 5.9667 |

*Source: own elaboration*

## Hypotheses Testing

### *Effects of Sponsorship Disclosure Format and Influencer Compensation Nature (H1a, H1b, and H1)*

A two-way ANOVA was conducted with sponsorship disclosure format and compensation nature as between-subject factors. Three sponsorship disclosure formats (implicit, explicit, and explicit combined with Instagram's "Paid Partnership" tag) were crossed with two compensation types (financial and in-kind), yielding six active experimental conditions. An additional baseline condition (n = 60) received no disclosure and no compensation information, serving as a reference point for post-hoc comparisons. Due to the incomplete factorial structure, whereby the no-disclosure condition existed only in combination with no compensation, the two-way ANOVA was conducted on the six active conditions. Results revealed a significant main effect of sponsorship disclosure format on perceived sponsorship transparency ($F(2) = 3.114$, $p = .041$), confirming H1a. Explicit disclosures and those combined with Instagram's "Paid Partnership" tag generated significantly higher transparency perceptions than the no-disclosure baseline. Compensation nature showed no significant main effect ($F(1) = 0.654$, $p = .401$), rejecting H1b. The interaction effect was also non-significant ($F(2) = 0.443$, $p = .654$), indicating that sponsorship disclosure format and compensation nature operate independently rather than jointly, partially challenging the premise of H1 (Table 7)

Post-hoc Scheffé tests revealed that the only significant pairwise difference was between the no-disclosure baseline and explicit disclosure combined with Instagram's "Paid Partnership" tag (difference = 0.37), suggesting explicit disclosure alone does not substantially affect transparency perceptions unless reinforced by the platform tag (Table 8).

Table 7

**Tests of Between-Subject Effects**

| | Sum of squares | df | Mean Square | F | Sig. | Hypothesis result |
|---|---|---|---|---|---|---|
| Sponsorship Disclosure Format | 4.019 | 2 | 2.009 | 3.114 | 0.041 | Supported |
| Compensation nature | 0.416 | 1 | 0.416 | 0.654 | 0.401 | Not supported |
| Sponsorship Disclosure Format X Compensation Nature | 0.564 | 2 | 0.282 | 0.443 | 0.654 | Not supported |

*Source: own elaboration*

Table 8

**Post-Hoc Analysis of The Significant Differences**

| Sponsorship Disclosure Format (A) | Sponsorship Disclosure Format (B) | Difference (A-B) | Standard Error | Sig. |
|---|---|---|---|---|
| No Disclosure | Implicit Disclosure | -0.1126 | 0.13013 | 0.840 |
| | Explicit Disclosure | -0.2759 | 0.13198 | 0.207 |
| | Explicit Disclosure Combined with IG Tool | -0.3746* | 0.13037 | 0.038 |
| Implicit Disclosure | No Disclosure | 0.1126 | 0.13013 | 0.840 |
| | Explicit Disclosure | -0.1663 | 0.10696 | 0.471 |
| | Explicit Disclosure with IG Tool | -0.2603 | 0.10502 | 0.101 |
| Explicit Disclosure | No Disclosure | 0.2759 | 0.13198 | 0.207 |
| | Implicit Disclosure | 0.1663 | 0.10696 | 0.471 |
| | Explicit Disclosure with IG Tool | -0.0922 | 0.10704 | 0.847 |
| Explicit Disclosure Combined with IG Tool. | No disclosure | 0.3746* | 0.13037 | 0.038 |
| | Implicit Disclosure | 0.2603 | 0.10502 | 0.101 |
| | Explicit Disclosure | 0.0922 | 0.10704 | 0.847 |

*Source: own elaboration*

### *Relationships between Perceived Sponsorship Transparency, Credibility, and Customer Responses (H2–H5b)*

*Simple Regression*

Simple regression confirmed all hypotheses (H2–H5b) with statistical significance ($p < .001$). Perceived sponsorship transparency positively influenced source credibility ($\beta = 0.337$, $t = 6.98$, $R^2 = 0.11$) and information credibility ($\beta = 0.241$, $t = 5.03$, $R^2 = 0.054$), confirming H2 and H3, though transparency impacted source credibility more strongly than information credibility. Source credibility strongly predicted online engagement ($\beta = 0.791$, $t = 26.89$, $R^2 = 0.633$) and purchase intention ($\beta = 0.817$, $t = 28.69$, $R^2 = 0.666$), confirming H4a and H4b. Information credibility positively predicted online engagement ($\beta = 0.599$, $t = 14.09$, $R^2 = 0.349$) and purchase intention ($\beta = 0.572$, $t = 14.95$, $R^2 = 0.366$), confirming H5a and H5b (Table 9)

*Stepwise Multiple Regression*

Stepwise regression was conducted as an exploratory complement to hypothesis testing to identify which dimensions of perceived sponsorship transparency and source credibility most strongly predicted dependent variables. Since these dimensions are conceptually parallel rather than hierarchically ordered, stepwise regression was retained as the most appropriate method for identifying relative predictive importance without imposing an arbitrary entry sequence. Results should be interpreted as indicative of construct dimension importance rather than definitive causal hierarchies.

For H2, disclosure ($\beta = 0.36$) and lack of deception ($\beta = 0.25$) positively predicted source credibility, while brand presence showed a slight negative effect ($\beta = -0.10$, $p = .029$). For H3, brand presence ($\beta = 0.09$, $p = .046$) and disclosure ($\beta = 0.26$, $p < .001$) predicted information credibility, with lack of deception removed due to insignificance.

Table 9

**Statistical significance of the model (H2, H3, H4a, H4b, H5a, and H5b)**

| Hypothesis | Independent Variable | Dependent Variable | F | Sig. | R Square | B | Std. Error | Beta | t | Hypothesis Result |
|---|---|---|---|---|---|---|---|---|---|---|
| H2 | Perceived Sponsorship Transparency | Source Credibility | 46.789 | 0.000 | 0.109 | 0.495 | 0.069 | 0.337 | 6.983 | Confirmed |
| H3 | Perceived Sponsorship Transparency | Information Credibility | 25.386 | 0.000 | 0.054 | 0.338 | 0.057 | 0.241 | 5.026 | Confirmed |
| H4a | Source Credibility | Online Engagement | 739.586 | 0.000 | 0.633 | 1.273 | 0.042 | 0.791 | 26.892 | Confirmed |
| H4b | Source Credibility | Purchase Intention | 793.189 | 0.000 | 0.666 | 1.215 | 0.037 | 0.817 | 28.688 | Confirmed |
| H5a | Information Credibility | Online Engagement | 265.086 | 0.000 | 0.349 | 1.016 | 0.054 | 0.599 | 14.089 | Confirmed |
| H5b | Information Credibility | Purchase Intention | 248.073 | 0.000 | 0.366 | 0.979 | 0.058 | 0.572 | 14.948 | Confirmed |

*Source: own elaboration*

Table 10

**Statistical significance of the stepwise model (H3a, H3b, H4a, and H4b)**

| Hypothesis | Independent Variable | Dimension | Beta | t | Sig. | Dependent Variable |
|---|---|---|---|---|---|---|
| H2 | Perceived Sponsorship Transparency | Disclosure | 0.362 | 7.587 | 0.000 | Source Credibility |
| | | Lack of Deception | 0.249 | 5.545 | 0.000 | |
| | | Brand Presence | -0.102 | -2.138 | 0.029 | |
| H3 | Perceived Sponsorship Transparency | Disclosure | 0.259 | 5.417 | 0.000 | Information Credibility |
| | | Brand Presence | 0.088 | 1.951 | 0.046 | |
| H4a | Source Credibility | Attractiveness | 0.103 | 2.617 | 0.008 | Online Engagement |
| | | Expertise | 0.237 | 6.193 | 0.000 | |
| | | Similarity | 0.566 | 14.561 | 0.000 | |
| H4b | Source Credibility | Expertise | 0.307 | 8.784 | 0.000 | Purchase Intention |
| | | Similarity | 0.561 | 17.381 | 0.000 | |

*Source: own elaboration*

Table 11

**Removed dimensions from the stepwise model:**

| Hypothesis | Independent Variable | Removed Dimension | t-value | Sig. |
|---|---|---|---|---|
| H3 | Perceived Sponsorship Transparency | Lack of Deception | 0.348 | 0.716 |
| H4a | Source Credibility | Trustworthiness | 1.583 | 0.103 |
| H4b | Source Credibility | Attractiveness | 1.935 | 0.052 |
| | | Trustworthiness | 1.528 | 0.117 |

*Source: own elaboration*

For H4a, expertise (β = 0.24), similarity (β = 0.57), and attractiveness (β = 0.10) predicted online engagement, with similarity as the strongest predictor. For H4b, only expertise (β = 0.31) and similarity (β = 0.56) predicted purchase intention (Tables 10 and 11).

### *Mediation Analysis (PROCESS Macro, Model 6)*

Serial mediation models tested whether perceived sponsorship transparency (M1), source credibility (M2), and information credibility (M3) mediated sponsorship disclosure format's impact on online engagement and purchase intention, with compensation nature as a covariate.

*Model 1* (disclosure → transparency → source credibility → online engagement) was significant ($R^2$ = .79, F = 189.28, p < .001), with a significant serial indirect effect (b = 1.97, 95% CI [0.91, 3.09]) and non-significant direct effect (b = 0.26, p = .70), supporting full mediation (Table 12).

*Model 2* (disclosure → transparency → source credibility → purchase intention) was significant ($R^2$ = .78, F = 180.27, p < .001), with a significant indirect effect (b = 1.31, 95% CI [0.60, 2.03]) and non-significant direct effect (b = 0.22, p = .63), confirming full mediation (Table 13).

*Model 3* (disclosure → transparency → information credibility → online engagement) explained 92% of engagement variance (F = 563.40, p < .001), with a significant indirect effect (b = 2.53, 95% CI [1.42, 3.68]) and non-significant direct effect (b = −0.80, p = .06) (Table 14).

*Model 4* (disclosure → transparency → information credibility → purchase intention) accounted for 91% of variance (F = 513.86, p < .001), with a significant indirect effect (b = 1.69, 95% CI [0.94, 2.48]) and non-significant direct effect (b = −0.51, p = .09) (Table 15).

The high explanatory power of Models 3 and 4 ($R^2$ = .92 for online engagement and $R^2$ = .91 for purchase intention) reflects the strong conceptual relationship between credibility perceptions and customer responses in influencer marketing contexts, when sponsored information is perceived as accurate and trustworthy, audiences are more likely to engage and consider product adoption (Lou & Yuan, 2019; Martínez-López et al., 2020). Robustness checks confirmed no significant multicollinearity (all VIF values < 5, tolerance > 0.20) and no substantial common method bias (Harman's single-factor test < 50% variance explained), with the between-subjects experimental design further reducing the likelihood of method-driven effects. Compensation nature showed slight negative effects on both credibility dimensions (p = .005) and a slight positive

Table 12

**Model 1 – Mediation through Transparency and Source Credibility (DV: Online Engagement)**

| Path | Effect (b) | SE | t | p | 95% CI |
|---|---|---|---|---|---|
| Sponsorship Disclosure Format → Transparency | 9.29 | 0.64 | 14.47 | <.001 | [8.02, 10.55] |
| Transparency → Source Credibility | 0.31 | 0.09 | 3.50 | .001 | [0.14, 0.49] |
| Source Credibility → Online Engagement | 0.68 | 0.04 | 18.30 | <.001 | [0.61, 0.75] |
| Direct Effect (Disclosure Type → Online Engagement) | 0.26 | 0.67 | 0.39 | .70 | [–1.06, 1.58] |
| Serial Indirect Effect (X → M1 → M2 → Y) | 1.97 | 0.55 | – | – | [0.91, 3.09] |
| Model $R^2$ (Online Engagement) | .79 | | | | |

*Source: own elaboration*

Table 13

**Model 2 – Mediation through Transparency and Source Credibility (DV: Purchase Intention)**

| Path | Effect (b) | SE | t | p | 95% CI |
|---|---|---|---|---|---|
| Sponsorship Disclosure Format → Transparency | 9.29 | 0.64 | 14.47 | < .001 | [8.02, 10.55] |
| Transparency → Source Credibility | 0.31 | 0.09 | 3.50 | .001 | [0.14, 0.49] |
| Source Credibility → Purchase Intention | 0.45 | 0.03 | 17.57 | < .001 | [0.40, 0.50] |
| Direct Effect (Disclosure Type → Purchase Intention) | 0.22 | 0.46 | 0.48 | .63 | [–0.69, 1.14] |
| Serial Indirect Effect (X → M1 → M2 → Y) | 1.31 | 0.36 | – | – | [0.60, 2.03] |
| Model $R^2$ (Purchase Intention) | .78 | | | | |

*Source: own elaboration*

Table 14

**Model 3 – Mediation through Transparency and Information Credibility (DV: Online Engagement)**

| Path | Effect (b) | SE | t | p | 95% CI |
|---|---|---|---|---|---|
| Sponsorship Disclosure Format → Transparency | 9.29 | 0.64 | 14.47 | < .001 | [8.02, 10.55] |
| Transparency → Information Credibility | 0.23 | 0.06 | 3.83 | < .001 | [0.11, 0.35] |
| Information Credibility → Online Engagement | 1.19 | 0.03 | 34.26 | < .001 | [1.12, 1.26] |
| Direct Effect (Disclosure Type → Online Engagement) | –0.80 | 0.42 | –1.90 | .059 | [–1.63, 0.03] |
| Serial Indirect Effect (X → M1 → M2 → Y) | 2.53 | 0.58 | – | – | [1.42, 3.68] |
| Model $R^2$ (Online Engagement) | .92 | | | | |

*Source: own elaboration*

Table 15

**Model 4 – Mediation through Transparency and Information Credibility (DV: Purchase Intention)**

| Path | Effect (b) | SE | t | p | 95% CI |
|---|---|---|---|---|---|
| Sponsorship Disclosure Format → Transparency | 9.29 | 0.64 | 14.47 | < .001 | [8.02, 10.55] |
| Transparency → Information Credibility | 0.23 | 0.06 | 3.83 | < .001 | [0.11, 0.35] |
| Information Credibility → Purchase Intention | 0.80 | 0.02 | 32.38 | < .001 | [0.75, 0.84] |
| Direct Effect (Disclosure Type → Purchase Intention) | –0.51 | 0.30 | –1.70 | .091 | [–1.10, 0.08] |
| Serial Indirect Effect (X → M1 → M2 → Y) | 1.69 | 0.39 | – | – | [0.94, 2.48] |
| Model $R^2$ (Purchase Intention) | .91 | | | | |

*Source: own elaboration*

impact on purchase intention (b = 0.74, p = .012), but did not strongly predict transparency (p > .18), leaving primary mediation patterns unaffected.

## Results Summary

Table 16 summarizes all hypothesis and mediation analysis results, presenting direct effects between constructs and indirect mediation paths tested using PROCESS Model 6, illustrating how perceived sponsorship transparency operates as the central mediating mechanism linking sponsorship disclosure format to credibility evaluations and subsequent customer responses.

with prior studies (Boerman et al., 2017; Carr & Hayes, 2014; De Veirman & Hudders, 2020; Evans et al., 2017; Kay et al., 2020; Wojdynski et al., 2018). Posts with clear hashtags like "#ad," "#sponsored," or Instagram's "Paid Partnership" tag are perceived as more transparent than undisclosed posts (Boerman & Müller, 2022), while abbreviated tags such as "#sp" were no more effective than no disclosure, demonstrating that ambiguous indicators fail to meet transparency expectations.

The findings highlight a distinction between hashtag and platform-integrated disclosure formats. While hashtag disclosures rely on influencer-generated signals, platform

Table 16

**Results Summary**

| Hypothesis | Relationship Tested | Direct Effect | Mediation Path (PROCESS Model 6) | Indirect Effect Result |
|---|---|---|---|---|
| H1 | Sponsorship Disclosure Format X Compensation Nature→ Perceived Sponsorship Transparency | Not Supported | – | – |
| H1a | Sponsorship Disclosure Format → Perceived Sponsorship Transparency | Supported | – | – |
| H1b | Influencer Compensation Nature → Perceived Sponsorship Transparency | Not Supported | – | – |
| H2 | Perceived Sponsorship Transparency → Source Credibility | Supported | Sponsorship Disclosure Format → Transparency → Source Credibility → Outcome | Supported (Full Mediation in Models 1 & 2) |
| H3 | Perceived Sponsorship Transparency → Information Credibility | Supported | Sponsorship Disclosure Format → Transparency → Information Credibility → Outcome | Supported (Full Mediation in Models 3 & 4) |
| H4a | Source Credibility → Online Engagement | Supported | Sponsorship Disclosure Format → Transparency → Source Credibility → online Engagement | Supported (Full Serial Mediation) |
| H4b | Source Credibility → Purchase Intention | Supported | Sponsorship Disclosure Format → Transparency → Source Credibility → Purchase Intention | Supported (Full Serial Mediation) |
| H5a | Information Credibility → Online Engagement | Supported | Sponsorship Disclosure Format → Transparency → Information Credibility → Online Engagement | Supported (Full Serial Mediation) |
| H5b | Information Credibility → Purchase Intention | Supported | Sponsorship Disclosure Format → Transparency → Information Credibility → Purchase Intention | Supported (Full Serial Mediation) |

*Source: own elaboration*

## Discussion

Results confirm that sponsorship disclosure format differentially influences perceived sponsorship transparency while compensation nature does not, consistent

disclosures represent standardized, system-supported cues functioning as institutional signals endorsed by the platform. This extends the Persuasion Knowledge Model beyond individual-level cues to include platform-level signals, and extends Communication Transparency Theory

by showing that perceived sponsorship transparency is shaped not only by influencer behavior but also by platform design.

Higher perceived sponsorship transparency strengthened both source and information credibility (Audrezet et al., 2020; Lou & Yuan, 2019), which in turn positively influenced online engagement and purchase intention (Lou et al., 2021; Martínez-López et al., 2020). Serial mediation analyses showed that perceived sponsorship transparency and credibility mediated disclosure format's influence on outcomes; direct effects were non-significant, indicating full mediation and confirming that transparency shapes credibility rather than directly triggering behavior.

The study contributes by establishing perceived sponsorship transparency as a key psychological intermediary linking disclosure format to credibility and outcomes. The findings extend PKM by showing that disclosure-triggered persuasion knowledge does not necessarily generate resistance; when perceived as open and sincere, it enhances credibility, reframing persuasive intent as relational honesty. Communication Transparency Theory and Parasocial Interaction Theory are reinforced by demonstrating that transparent communication strengthens trust driving credibility and behavior. Platform-integrated disclosures function as institutional transparency signals, and the serial mediation pathway positions perceived sponsorship transparency as a layered evaluative process shaped by influencer behavior, message content, and platform design.

From a practical perspective, influencers and brands should adopt explicit, standardized disclosure formats using platform tools such as Instagram's "Paid Partnership" tag to reduce skepticism, promote engagement, and foster trust.

The study relied on non-probability snowball sampling, limiting representativeness and introducing homogeneity bias. Approximately 21% of respondents identified as influencers, which may have influenced responses due to higher persuasion knowledge. Future research should examine whether respondent type moderates perceived sponsorship transparency. The use of a fictitious influencer strengthened internal validity but reduced ecological validity, as real-world contexts involve established trust and brand equity. The study also examined only two compensation forms and primarily Instagram users aged 18–39, limiting generalizability.

Stepwise regression was retained because construct dimensions are conceptually parallel rather than hierarchical, though results should be interpreted as indicative rather than causal. While CFA would ideally validate the three-dimensional transparency structure, exploratory factor analysis showed strong adequacy (KMO = 0.893, $p < .001$), high explained variance (87.4%), and satisfactory reliability ($\alpha = 0.779–0.888$), though the absence of CFA remains a limitation.

Future research could examine transparency across platforms such as YouTube or TikTok (De Jans et al., 2018), explore moderators like authenticity and skepticism (Boerman & Müller, 2022), and use longitudinal and probability-based designs. Studies using real influencer–brand collaborations and broader compensation structures would improve ecological validity and generalizability.

## Conclusion

This study examined perceived sponsorship transparency in influencer marketing among Instagram micro-influencers. Sponsorship disclosure format influences perceived transparency, with explicit disclosures increasing transparency while implicit or absent disclosures do not; compensation nature had no significant effect. Perceived sponsorship transparency positively influenced source and information credibility, which in turn increased engagement and purchase intention.

Serial mediation confirmed that disclosure format influences outcomes through transparency and credibility, establishing perceived sponsorship transparency as the key mechanism. Explicit disclosures combined with Instagram's "Paid Partnership" tag produced the strongest transparency perceptions, while implicit disclosures performed similarly to no disclosure. Source credibility emerged as a stronger mediator, indicating that audiences evaluate the influencer before the message, and that transparency is an active evaluative stage.

Theoretically, the findings extend PKM by showing that transparent disclosure reframes persuasive intent as relational honesty rather than generating resistance, and support Communication Transparency and Parasocial Interaction theories by confirming that openness reinforces trust. Practically, perceived sponsorship transparency serves as a strategic tool: explicit disclosures enhance credibility while preserving relationships and supporting ethical, compliant marketing.

Future research should examine perceived sponsorship transparency effects across influencer tiers, platforms, and sponsorship formats, consider the role of brand life cycle, and explore partnership duration, behavioral data, and longitudinal designs to validate findings across broader influencer marketing contexts. Ultimately, perceived sponsorship transparency represents a sustainable pathway toward both ethical and effective influencer marketing, demonstrating that openness and persuasion can coexist rather than conflict.

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# ROLES OF INDUSTRY ASSOCIATIONS IN INDUSTRIAL ECOSYSTEMS – THE CASE OF HUNGARIAN BATTERY ASSOCIATION

# AZ IPARÁGI SZÖVETSÉGEK SZEREPE AZ IPARI ÖKOSZISZTÉMÁKBAN – A MAGYAR AKKUMULÁTOR SZÖVETSÉG ESETE

Industry associations play important roles in industrial ecosystems, yet their multiple functions are difficult to capture through a single theoretical perspective. This study examines the role configuration of the Hungarian Battery Association and evaluates the explanatory contributions of industrial network management, meta-organization theory, and civil society organization scholarship. Using a single-case design, the authors conducted a deductive codebook thematic analysis of HUBAs activities from its inception in 2021 to 2026. They find that all roles identified by industrial network management and meta-organization theory are evident in HUBA's activities, but their presence varies while some roles predicted by CSO literature were either absent or partially evident in HUBA's activities. The findings reveal that the same organization activity can fulfil theoretically distinct roles depending on their purpose, beneficiaries, and relational context. The study shows that combining the three perspectives provides a more comprehensive functional explanation of industry associations operating within strategic industrial ecosystems.

Keywords: **battery industry, industry associations, organizational roles, meta-organizations, industrial network management, civil society organizations**

Az iparági szövetségek fontos szerepet töltenek be az ipari ökoszisztémákban, ugyanakkor betöltött funkcióik nehezen ragadhatók meg egyetlen elméleti megközelítés segítségével. E tanulmány a Magyar Akkumulátor Szövetség (HUBA) szerepkonfigurációját vizsgálja, valamint értékeli az ipari hálózatmenedzsment, a metaorganizációs elmélet és a civil társadalmi szervezetek szakirodalmának magyarázó erejét. A szerzők kutatása egy esetre épül, amely során deduktív kódalapú tematikus elemzést végeztek a szervezet tevékenységeiről a 2021-es megalakulásától 2026-ig terjedő időszakban. Eredményeik szerint az ipari hálózatmenedzsment és a metaorganizációs elmélet által azonosított valamennyi szerep megjelenik a HUBA tevékenységében, bár eltérő mértékben, míg a civil szervezetek szakirodalmában meghatározott egyes szerepek hiányoznak, vagy csak részlegesen figyelhetők meg a HUBA működésében. Eredményeik kiemelik, hogy ugyanazon szervezeti tevékenység céljától, kedvezményezettjeitől és kapcsolati kontextusától függően eltérő elméleti szerepeket tölthet be. A tanulmány rámutat arra, hogy a három megközelítés együttes alkalmazása átfogóbb magyarázatot nyújt a stratégiai jelentőségű ipari ökoszisztémákban működő iparági szövetségek funkcióira.

Kulcsszavak: akkumulátoripar, iparági szövetségek, szervezeti szerepek, metaszervezetek, ipari hálózatmenedzsment, civil szervezetek

**Funding/Finanszírozás:**
This research was supported by the project NKFI-OTKA K No. 143238 „New European industrial strategy and the Central and Eastern European growth model".
A kutatást az NKFI-OTKA K 143238 sz. Új európai ipari stratégia és a közép- és kelet-európai növekedési modell című projekt támogatta.

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The article was received: 12. 03. 2026, revised: 13. 07. 2026, 20. 07. 2026 and 31. 08. 2026, accepted: 04. 09. 2026.
A cikk beérkezett: 2026. 03. 12-én, javítva: 2026. 07. 13-án, 2026. 07. 20-án és 2026. 08. 31-én, elfogadva: 2026. 09. 04-én.

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The battery ecosystem is recognized by the European Union (EU) as a strategic industrial ecosystem underpinning the green transition, industrial competitiveness, and strategic autonomy (EC, 2017; EC, 2020). Like other emerging industrial ecosystems, it involves interdependent public and private actors, from raw material suppliers and manufacturers to universities, research organizations, governments, and recycling firms, whose collective capabilities are required to generate value across the entire value chain (Jacobides et al., 2018). Consequently, organizations capable of coordinating relationships across organizational boundaries have become increasingly important, as no single actor can independently coordinate the capabilities required to develop a competitive battery industry (Möller & Halinen, 1999; EC, 2019; Gieschen et al., 2021).

Recognizing the coordination challenges associated with emerging strategic industrial ecosystems, both the EU and national governments have increasingly promoted ecosystem-based governance mechanisms to mitigate fragmentation. At the EU level, initiatives such as the European Battery Alliance (EBA) were established to coordinate heterogeneous actors across the battery value chain, while national-level associations have been established to pursue similar objectives (EC, 2017; EC, 2020; Gieschen et al., 2021). For instance, Hungary's National Battery Industry Strategy, adopted in 2021, recognizes industry alliances as important coordination mechanisms and identifies the Hungarian Battery Association (HUBA) as a key coordinating organization (ITM, 2021; Patrizio et al., 2020; Wu, 2024; Czirfusz, 2023). The Strategy specifically states that HUBA should "continue coordination and dialogue between stakeholders along the entire value chain" and continuously monitor the implementation of the national action plan (ITM, 2021, p. 140).

Industry associations represent one form of intermediary organization that can address coordination challenges within industrial ecosystems. Within such ecosystems, these organizations coordinate interactions and value creation (Möller & Halinen, 1999; Aarikka-Stenroos & Halinen, 2007), while facilitating collaboration, knowledge exchange, capability development, policy coordination, and collective action across organizational boundaries (Dóra & Szalkai, 2021; Alo & Arslan, 2023; Berkowitz & Souchaud, 2024). Sustainability transition research further highlights the contribution of intermediary organizations, including meta-organizations and civil society organizations (CSOs), in mobilizing collective responses to societal challenges (Hoff et al., 2020; Berkowitz & Bor, 2024; WEF, 2023).

Despite growing recognition of the roles these organizations can play in emerging ecosystems and sustainability transitions, limited empirical research has examined how intermediary organizations combine and perform multiple roles within emerging strategic industrial ecosystems such as the battery ecosystem. Existing studies of the Hungarian battery industry have primarily focused on industrial development, foreign direct investment, electromobility, and system-level analyses of the domestic and international battery value chain in Hungary (Czirfusz, 2023; Kun, 2025; Yang, 2024). However, the roles performed by industry associations within the sector remain largely unexplored.

Beyond this empirical gap, a broader theoretical gap remains concerning how industry associations' roles can be understood. Existing research conceptualizes industry associations through several complementary but largely disconnected perspectives. Industrial network management views them as boundary-spanning intermediary organizations that facilitate coordination, resource allocation, and value creation within inter-organizational networks (Möller & Halinen, 1999; Aarikka-Stenroos & Halinen, 2007; Szalkai & Dóra, 2020). Meta-organization theory explains how organizations composed of organizational members govern collective action, represent member interests, and coordinate autonomous actors (Ahrne & Brunsson, 2008; Berkowitz et al., 2022). Civil society organization scholarship highlights the broader societal and public-value roles that non-state, non-profit organizations may perform, including advocacy, representation, capacity building, and standard setting (WEF, 2023; Hoff et al., 2020). Although these perspectives identify overlapping organizational roles, they differ in their assumptions regarding organizational purpose, governance, and behaviour. To date, few empirical studies have examined how these perspectives can be integrated to explain the role configurations of industry associations operating within strategic industrial ecosystems.

HUBA represents an especially relevant case because it exhibits characteristics associated with all three perspectives. Structurally, it exhibits characteristics of a meta-organization because its members are organizations rather than individuals. Legally, it is registered as a civil society organization under Hungarian law. Functionally, it operates as an intermediary organization embedded within both the Hungarian and wider European battery ecosystems. Rather than privileging a single theoretical perspective, this study adopts a multi-theoretical analytical framework to examine how industry associations enact multiple roles within emerging strategic industrial ecosystems using HUBA as a case study. Specifically, the study addresses the following research questions:

RQ1: What role configuration does the Hungarian Battery Association exhibit within Hungary's battery ecosystem?

RQ2: To what extent do industrial network management, meta-organization theory, and civil society organization scholarship explain the observed role configuration of the Hungarian Battery Association?

By examining HUBA through the complementary lenses of industrial network management, meta-organization theory, and civil society organization scholarship, this study contributes to literature in two ways. Empirically, it provides a systematic analysis of the role configuration of an industry association within an emerging strategic battery ecosystem. Theoretically, it demonstrates how integrating these three perspectives provides a more comprehensive understanding of intermediary organizations than any single perspective alone.

The remainder of the article is structured as follows. The next section discusses the theoretical underpinnings of the study, followed by the research design and analytical methods used to empirically examine HUBA's roles and activities. The key findings are then presented, before the article concludes with recommendations.

## Theoretical perspectives on industry association roles

Over time, scholars have used a range of terms – including industry associations, alliances, networks, federations, umbrella organizations, consortia, unions, and meta-organizations – to describe organizations that facilitate collective action among firms and other organizations (Grandori, 1997; Barringer & Harrison, 2000; Reveley & Ville, 2010; Berkowitz, 2026). Although these labels are sometimes used interchangeably, Ahrne and Brunsson (2008) note that they are often applied without clearly distinguishing their theoretical foundations although terminologies may reflect different structural characteristics, governance arrangements, and organizational purposes. Consequently, similar coordinating organizations may be conceptualized differently depending on whether emphasis is placed on membership structure, governance mechanisms, network position, legal status, or broader societal functions.

This conceptual diversity is particularly evident in the study of industry associations. Although industry associations are increasingly recognized as important actors within strategic industrial ecosystems, they have been conceptualized through different theoretical perspectives. For instance, industry associations have been conceptualized as intermediary organizations embedded within industrial networks, as meta-organizations, and as civil society organizations. Each perspective captures different dimensions of industry associations and, consequently, highlights different organizational roles.

### Industrial Network Management Perspective

Industrial network management is concerned with how organizations manage their relationships, activities and positions within networks of interdependent actors (Håkansson & Ford, 2002; Möller & Halinen, 1999). From this perspective, industrial networks consist of configurations of actors, resources and activities, where actors involved need not be limited to firms but may also include governmental agencies, universities, research institutions and other noncommercial organizations or individuals (Möller & Halinen, 1999).

Since the late 1980s, researchers in various fields have sought to understand organizations' abilities to manage relationships and operate within networks of organizations linked through economic and other forms of exchange (Knight & Harland, 2005; Hoványi, 2008; Baksa & Drótos, 2021). Snow et al. (1992) emphasized responsibilities related to network design, coordination and the maintenance of long-term collaborative relationships. Knight and Harland (2005) subsequently extended this perspective by highlighting the importance of coordination, information brokerage, innovation facilitation and strategic guidance within supply networks. Similarly, Järvensivu and Möller (2009) examined how network actors frame collaboration, mobilize stakeholders, activate participation and synthesize diverse interests to facilitate collective action.

Although these studies emerged from different streams of network research, they share a common concern with understanding how organizations facilitate interaction and

Table 1

**Industrial network management roles and their typical manifestations in industry associations**

| Network management role | Definition | Typical manifestations |
|---|---|---|
| Motivating | Encouraging network participants to engage actively in collaborative activities and remain committed to shared objectives. | Encouraging participation; stimulating member engagement; building commitment; promoting collaborative behaviour. |
| Resourcing | Identifying, acquiring and mobilizing the financial, human, technological and informational resources required for network activities. | Resource mobilization; acquiring funding; mobilizing expertise; facilitating access to resources; mobilizing complementary capabilities. |
| Goal setting and refining | Establishing and continuously refining the shared objectives, priorities and strategic direction of the network. | Defining common goals; strategic planning; developing shared visions; refining network priorities. |
| Consolidating | Strengthening relationships and maintaining long-term stability and cohesion of the network. | Building trust; integrating stakeholder interests; strengthening partnerships; maintaining cooperation; resolving conflicts. |
| Coordinating | Organizing and aligning activities of multiple autonomous organizations to facilitate collective action. | Organizing interactions; facilitating communication; coordinating joint activities; linking network actors. |
| Controlling | Monitoring network activities and ensuring that agreed rules, responsibilities and governance arrangements are followed. | Monitoring progress; establishing rules; evaluating performance; ensuring accountability and compliance. |
| Leveraging | Using and combining the knowledge, relationships and capabilities created within the network to generate additional value. | Applying shared knowledge; combining capabilities; disseminating learning; exploiting network relationships; facilitating innovation. |

*Source: adapted from Aarikka-Stenroos et al. (2017)*

collaboration among multiple autonomous actors. This differs from social network research, which is primarily concerned with the structure of relationships among actors, patterns of interaction and actors' positions within networks (Borgatti & Foster, 2003; Borgatti et al., 2009; Csonka, 2011; Mandják & Szántó, 2011; Vicsek et al., 2016).

Building on these different streams of network research, Aarikka-Stenroos et al. (2017) synthesized insights from strategic network literature, innovation network studies and industrial marketing and purchasing research into a comprehensive framework of network-management activities. The resulting framework identifies seven interrelated network-management activities: motivating, resourcing, goal setting and refining, consolidating, coordinating, controlling, and leveraging (Table 1).

This framework is particularly relevant to emerging strategic industrial ecosystems such as the battery ecosystem because these contexts involve heterogeneous actors including manufacturers, suppliers, research organizations, universities, public authorities, investors, regulators and industry associations. As Aarikka-Stenroos et al. (2017) argue, increasing actor diversity expands the resources available for innovation while making coordination substantially more challenging. Under such conditions, intermediary organizations can support collective action by mobilizing participants, integrating complementary capabilities, facilitating collaboration and maintaining relationships across organizational boundaries (Aarikka-Stenroos & Halinen, 2007).

## Meta-organization perspective

While industrial network management explains how organizations coordinate relationships within inter-organizational networks, meta-organization theory provides a complementary perspective by focusing on organizations whose members are organizations (Ahrne & Brunsson, 2008; Berkowitz et al., 2022). From this perspective, meta-organization is an analytical category rather than a formal designation. Consequently, entities described as industry associations, alliances, consortia or networks may be considered meta-organizations insofar as their members are organizations (Berkowitz, 2026).

Unlike conventional organizations, meta-organizations coordinate legally autonomous organizations that retain their own identities, decision-making authority and objectives. As a result, coordination relies more heavily on negotiation, collective decision-making and the alignment of member interests (Ahrne et al., 2016; Berkowitz & Grothe-Hammer, 2022). Meta-organizations operate across diverse sectors (Ahrne & Brunsson, 2008) and geographical scales (Berkowitz et al., 2022), industry associations represent one of the most prevalent forms of meta-organizations (Berkowitz, 2026).

While early research primarily emphasized the structural characteristics of meta-organizations, more recent scholarship has increasingly focused on their activities. Building on Ahrne and Brunsson (2008), Berkowitz et al. (2022) identify four broad meta-organizational activities: governance and co-management, advocacy, boundary and category work, and service provision (Table 2).

*Governance and co-management* involve coordinating autonomous member organizations through collectively established decision-making arrangements. Because member organizations retain their identities and autonomy, meta-organizational governance relies on joint decisions, agreed rules and other collectively established mechanisms rather than conventional hierarchical authority (Ahrne et al., 2016; Berkowitz et al., 2022).

*Advocacy* involves representing members' collective interests, influencing regulatory environments, participating in policy processes and acting as the collective voice of an industry (Berkowitz et al., 2022). *Boundary and category work* includes defining membership boundaries, constructing collective identities and categories, and contributing to the legitimacy and institutional development of industries (Ahrne & Brunsson, 2008; Ahrne et al., 2016; Berkowitz et al., 2022), while *service provision* covers activities aimed at strengthening members' capabilities, including knowledge sharing, research, training and other support activities (Berkowitz et al., 2022).

Meta-organizations may pursue multiple objectives simultaneously; therefore, the activities they perform are neither discrete nor mutually exclusive (Ahrne & Brunsson, 2008; Dumez & Renou, 2020). Recent research

Table 2

**Meta-organization roles and their typical manifestations in industry associations**

| Meta-organizational role | Definition | Typical manifestations |
|---|---|---|
| Governance and co-management | Facilitating interaction, collective decision-making and the joint management of relationships among autonomous member organizations | Membership rules; governing bodies; committees and working groups; collective decision-making; coordination of joint initiatives. |
| Advocacy | Representing and advancing the collective interests of members in relation to governments and external stakeholders. | Lobbying; position papers; stakeholder representation; policy dialogue; public communication |
| Boundary and category work | Establishing organizational and field boundaries and constructing the identity, categories, status and legitimacy of a collective or industry. | Membership boundaries; sector classification; industry identity; category construction; legitimacy building; field definition. |
| Service provision | Strengthening members' capabilities through the provision of services, information and shared resources. | Knowledge sharing; research; training; capacity building; resource mobilization; resource allocation. |

*Source: adapted from Ahrne and Brunsson (2008) and Berkowitz et al. (2022)*

suggests that the extent to which meta-organizations are able to perform their governance and co-management, advocacy, boundary and category work, and service provision roles depends on the resources available to them (Bor & Cropper, 2023). The roles of meta-organizations have become increasingly relevant within sustainability transitions and emerging industrial ecosystems, where complex system-level challenges require collaboration among heterogeneous organizations and the combination of complementary capabilities and resources (Valente & Oliver, 2018; Berkowitz et al., 2022; Berkowitz & Bor, 2024; Berkowitz & Souchaud, 2024).

## Civil society organization perspective

Although civil society organizations (CSOs) are commonly equated with non-governmental organizations (NGOs), they encompass a broader range of voluntary and associational organizations, including professional and business associations, trade unions, coalitions, umbrella organizations, academic and research institutions, and network organizations (Edwards, 2011; Guénéheux & Bottomley, 2014; Salamon et al., 2017; UIA, 2023; WEF, 2013; 2023). Civil society scholarship examines these diverse forms of voluntary collective action and their broader societal roles (Edwards, 2011; Hoff et al., 2020).

The World Economic Forum identifies ten distinct, but interconnected roles (Table 3) performed by civil society actors: service provider, advocate, watchdog, expert, capacity builder, incubator, representative, citizenship champion, solidarity supporter, and definer of standards (WEF, 2013).

The CSO roles should not be viewed as mutually exclusive, as contemporary civil society actors may perform overlapping functions, often in collaboration with business, government and other stakeholders (WEF, 2013). Given HUBA's legal status as a civil association, the CSO perspective is applied as a functional lens to examine the extent to which these broader societal roles are evident in its activities.

Table 3

**CSO roles and their typical manifestations**

| CSO role | Definition | Typical manifestations |
|---|---|---|
| Service provider | Delivering services that address societal needs and complement public and private sector activities. | Provision of societal services; project implementation; technical assistance; community support. |
| Advocate | Raising awareness of societal issues and advocating for policy or institutional change. | Public-interest advocacy; policy engagement; public campaigns; position papers addressing societal issues. |
| Watchdog | Holding institutions to account and promoting transparency and accountability. | Independent monitoring; public reporting; scrutiny; accountability initiatives. |
| Expert | Generating, disseminating and applying knowledge to inform policy and practice. | Research; knowledge sharing; expert advice; evidence generation. |
| Capacity builder | Strengthening the capabilities of organizations, communities and stakeholders. | Training; education; workshops; mentoring; technical support. |
| Incubator | Developing and supporting solutions that require relatively long development or payback periods. | Development and testing of long-term solutions; pilot initiatives; experimentation; support for emerging solutions. |
| Representative | Giving voice and influence to marginalized or under-represented groups. | Representation of marginalized constituencies; inclusive consultation; amplifying under-represented voices. |
| Citizenship champion | Promoting civic participation, inclusion and democratic engagement. | Citizen participation; civic engagement; rights awareness; public dialogue. |
| Solidarity supporter | Promoting fundamental and universal values. | Promotion of shared societal values; values-based campaigns; social solidarity; coalition building around societal principles. |
| Definer of standards | Contributing to the development and promotion of ethical, professional or industry standards. | Standards development; codes of conduct; best-practice guidelines; development of professional or industry norms. |

*Source: adapted from WEF (2013)*

## A multi-theoretical analytical framework for analysing industry association roles

The preceding sections indicate that industrial network management, meta-organization theory, and civil society organization scholarship provide distinct but complementary perspectives on the role of industry associations and their activities. Table 4 synthesizes the three perspectives by identifying areas of conceptual correspondence and divergence together with the illustrative manifestations of each role.

As indicated in Table 4, one area of conceptual correspondence relates to advocacy. Within the meta-organization perspective, advocacy refers to the representation of members' collective interests in relation to governments, regulators and other external stakeholders (Berkowitz et al., 2022), whereas civil society advocacy concerns broader societal issues and policy or institutional change (WEF, 2013). Thus, similar activities may appear across perspectives while differing in their purpose, intended beneficiaries and relational context.

A similar distinction is evident in knowledge-related activities. The CSO *expert* role emphasizes the generation and application of expertise, network *leveraging* concerns

Table 4

**Multi-theoretical analytical framework for analysing industry association roles**

| CSO role | Network management role | Meta-organizational role | Illustrative indicators |
|---|---|---|---|
| Solidarity supporter | Consolidating* | Governance and co-management* | Shared values; relationship building; collective participation |
| – | Coordinating | Governance and co-management | Interaction; communication; joint activities; collective decision-making |
| – | Motivating | – | Participation; engagement; commitment |
| Watchdog | Controlling* | – | Independent monitoring; accountability; compliance monitoring |
| Definer of standards | Goal setting and refining* | Boundary and category work* | Standards; strategic priorities; classifications; industry boundaries |
| Representative | – | Advocacy* | Under-represented voices; collective member representation |
| Advocate | – | Advocacy* | Policy change; lobbying; policy dialogue; member-interest representation |
| Expert | Leveraging* | Service provision* | Research; expert knowledge; knowledge sharing; information services |
| Capacity builder | – | Service provision* | Training; education; capability development; technical support |
| Service provider | Resourcing* | Service provision* | Societal services; resource mobilization; shared member services |
| Citizenship champion | – | – | Citizen participation; civic engagement; rights awareness |
| Incubator | – | – | Long-term solutions; experimentation; solution development |

*Note: * indicates partial conceptual correspondence. Roles appearing in the same row are not treated as theoretically equivalent. The original role definitions and manifestations presented in Tables 1–3 guided classification, with the purpose, intended beneficiaries and relational context of each activity considered when distinguishing theoretically similar roles.*

*Source: authors' synthesis based on Aarikka-Stenroos et al. (2017), Ahrne and Brunsson (2008), Berkowitz et al. (2022), and WEF (2013, 2023)*

facilitating access to and utilization of knowledge and other resources, while meta-organizational *service provision* captures the provision of knowledge-based services to members (Aarikka-Stenroos et al., 2017; Berkowitz et al., 2022; WEF, 2013). Thus, knowledge-related activities may correspond to all three perspectives, but for different theoretical reasons. At the same time, roles such as *citizenship champion* are unique to the CSO perspective and would not be captured by focusing solely on the network-management or meta-organization perspective.

In view of the above, this study adopts a multi-theoretical analytical framework for investigating the role configuration of HUBA. Rather than integrating overlapping roles into a new taxonomy, the framework preserves the theoretical meaning of the roles within each perspective. The roles summarized in Table 4 constitute the analytical framework and provide the deductive basis for coding the empirical evidence, while the conceptual distinctions guide the interpretation of activities that potentially correspond to roles across more than one perspective.

## Methodology and Research Design

This study adopts a qualitative single-case study design to investigate the role configuration of the Hungarian Battery Association within the emerging Hungarian battery ecosystem. This design is appropriate because the case study approach enables an in-depth investigation of a contemporary phenomenon within its real-life context (Yin, 2018).

### HUBA as the case organization

The Hungarian Battery Association was established in July 2021, the same year when Hungary adopted its National Battery Industry Strategy as a representative body for companies operating in the battery industry value chain (HUBA, 2023). As of July 2026, HUBA had 108 registered members (HUBA, 2026). Its membership comprises actors across the Hungarian battery value chain, including industrial firms (SMEs and local subsidiaries of multinational corporations), research and innovation organizations, and educational institutions.

HUBA is also a member of international networks including the European Battery Alliance and Eit InnoEnergy (HUBA, 2022, 2025). HUBA therefore provides an appropriate case for examining how an industry association performs multiple organizational roles within an emerging strategic industrial ecosystem characterized by heterogeneous actors.

### Data sources and collection

To enhance the credibility and contextual richness of the analysis, the study draws on multiple complementary sources of evidence. The primary dataset comprised documentary evidence of HUBA's activities, while semi-structured interviews and participant observations were used

as supplementary sources for contextualization and triangulation.

### *Documentary evidence*

The primary empirical dataset comprised 148 documentary records relating to HUBA's activities between its establishment in July 2021 and July 2026. These included HUBA's Articles of Association, official website publications, LinkedIn posts, reports, news items, policy documents and other publicly available organizational communications. These sources were selected because they provide a systematic and publicly verifiable record of the Association's activities. In addition, 62 emails distributed to all HUBA members between 10 October 2023 and 9 July 2024 were included; correspondence addressed only to individual members was excluded.

### *Semi-structured interviews and direct participant observation*

Supplementary evidence was obtained through two semi-structured interviews, one with HUBA's CEO and another with the CEO of a HUBA member organization. The interviews were used to clarify organizational processes and contextualize and triangulate interpretations derived from the documentary analysis.

Participant observation was also conducted at five major battery-industry events organized or attended by HUBA between 2023 and 2025 (Table 5). These observations provided additional contextual evidence on stakeholder interactions, networking activities and knowledge-sharing processes within the Hungarian battery ecosystem.

Table 5

**Events attended for participant observation**

| Event | Year | Appr. Number of participants |
|---|---|---|
| Hungarian Battery Day (Budapest, Hungary) | 2023, 2024, 2025 | 500 |
| Environmental Protection and Industrial Safety Conference (Visegrád, Hungary) | 2024 | 200 |
| Korea-Hungary Battery Industry Cooperation Forum (Budapest, Hungary) | 2024 | 200 |

*Source: authors' construct*

## Unit of analysis and analytical procedure

The study employed a theory-driven (deductive) codebook thematic analysis, which provides a structured framework suitable for applied and collaborative research (Braun & Clarke, 2021). Discrete organizational activities performed by HUBA constituted the units of coding and were analysed using the original role categories proposed by Aarikka-Stenroos et al. (2017), Berkowitz et al. (2022), and WEF (2013), as synthesized in Table 4. Analysis of the 148 documents identified 58 distinct organizational activities performed by HUBA. Since an activity could fulfil multiple purposes simultaneously, the same activity could be assigned to more than one role and interpreted across more than one theoretical perspective where supported by the original theoretical definitions.

Two co-authors initially analysed the documentary corpus using NVivo, while Microsoft Excel was used to organize the results. An additional co-author conducted a comparable analysis as a further validation step. This collaborative process facilitated comparison and interpretive convergence among researchers (Saldaña, 2013). Differences in interpretation were discussed among the co-authors and resolved by referring to the original theoretical definitions and the organizational purpose of the activity.

Although the analysis remained qualitative, descriptive frequency counts were calculated following the deductive coding process to indicate the relative prevalence of theoretically derived roles across the 58 organizational activities (Neuendorf, 2017). These frequencies were used to compare the prominence of roles within and across the three theoretical perspectives rather than for statistical inference. The key findings of the analyses are discussed next.

## Findings and discussions on the role configuration of Hungarian Battery Association

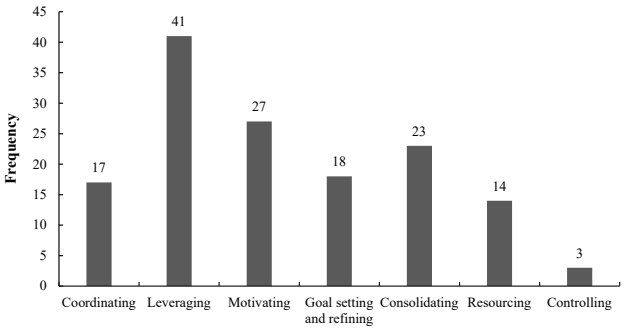
This section presents the findings in two parts, corresponding to the study's research questions. The first identifies HUBA's organizational role configuration, while the second evaluates the extent to which industrial network management, meta-organization theory and civil society organization scholarship explain the observed configuration.

### HUBA's role configuration from the industrial network management perspective

From the industrial network management perspective, we find that all seven network-management activities were evident in HUBA's role configuration, although their relative prevalence varied considerably. As shown in Figure 1, *leveraging* was the most frequently identified activity (41 occurrences), followed by *motivating* (27) and *consolidating* (23), whereas *controlling* was identified only three times.

Figure 1

**Industrial network management role profile of HUBA**




*Source: authors' analysis*

The observed configuration indicates that HUBA's network-management activities are oriented primarily towards leveraging resources and knowledge, encouraging actor participation in ecosystem activities, and strengthening relationships, while controlling was not prominent during the study period. Table 6 summarizes the empirical evidence for each network-management role and representative organizational activities.

Table 6

**Observed network management roles performed by HUBA**

| Network management role | Main empirical evidence | Representative organizational activities |
|---|---|---|
| Coordinating | Articles of Association; member emails; LinkedIn posts; conferences; participant observation | Working groups; Hungarian Battery Week; professional conferences; stakeholder forums; international cooperation |
| Leveraging | Emails; LinkedIn posts; Competence Map; publications; workshops | Knowledge sharing; competence mapping; technical presentations; newsletters; study visits |
| Motivating | Member emails; LinkedIn posts; invitations to events and consultations | Encouraging participation in consultations, workshops, conferences and working groups |
| Goal setting and refining | Articles of Association; AFIR position paper; regulatory consultations | Battery Strategy 2030; AFIR recommendations; regulatory input; industry roadmaps |
| Consolidating | Conferences; MoUs; international partnerships; working groups | Bringing together firms, universities, government bodies and international partners |
| Resourcing | Articles of Association; EIPP; laboratory; MoUs; funding calls | Grants; flagship projects; research infrastructure; laboratory equipment; project opportunities |
| Controlling | Articles of Association; membership framework; regulatory communication | Membership criteria; compliance communication; environmental responsibility |

*Source: authors' synthesis*

The dominant role, *leveraging*, was evident in HUBA's conferences, newsletters, technical guidance, digital knowledge platforms and exchanges among industrial, academic and governmental actors. Its knowledge-related dimension was also reflected in an interview with the CEO of a member organization, who explained that *"One of the important tasks of the Association is to educate its own members about the regulations, technological developments and opportunities affecting the battery industry."*

The *motivating* and *coordinating* roles were observed through HUBA's repeated invitations to consultations, workshops and events. For example, in relation to consultations by the European Union Agency for the Cooperation of Energy Regulators (ACER), members were invited by email to contribute individually or through HUBA's collective response.

*Goal setting and refining, consolidating,* and *resourcing* were also evident in activities related to Battery Strategy 2030, Hungarian Battery Week, thematic working groups, the European Industrial Partnership Programme, the Korea-Hungary Battery Cooperation Center and the Battery Laboratory Equipment Park (Table 6).

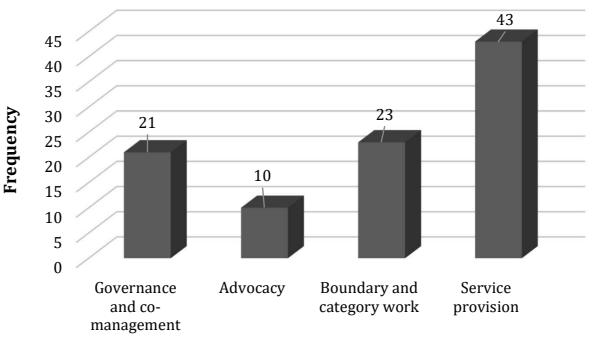
HUBA's observed activities closely correspond to the network-management framework of Aarikka-Stenroos et al. (2017). Although all seven activities were identified, the predominance of leveraging, motivating and consolidating indicates that the Association contributes primarily by mobilizing knowledge and other network resources, encouraging participation and strengthening collaborative relationships rather than through controlling activities. This pattern is consistent with network-management research emphasizing the importance of mobilizing resources and actors, stimulating collaboration, and building trust and cohesion among heterogeneous network participants (Möller & Halinen, 1999; Aarikka-Stenroos et al., 2017). It also aligns with research on intermediary actors showing that third actors can facilitate connections between otherwise separate organizations and enable access to resources that support inter-organizational collaboration (Aarikka-Stenroos & Halinen, 2007; Dóra & Szalkai, 2021). In addition, findings are consistent with Bengtsson and Kock (2000) who show that associations can play an intermediary role in managing relationships among firms that simultaneously cooperate and compete.

## HUBA's role configuration from the meta-organization perspective

From the meta-organization perspective, our analysis indicates that all four expected roles were evident in HUBA's activities, although their relative prevalence varied. As shown in Figure 2, service provision was the most frequently identified role (43 occurrences), followed by boundary and category work (23) and governance and co-management (21), while advocacy was less frequent (10).

Figure 2

**Meta-organizational role profile of HUBA**




*Source: authors' analysis*

The frequency distribution (Figure 2) indicates that HUBA's meta-organizational activities are oriented primarily towards providing collective services, defining and strengthening the emerging industry, and coordinating relations among autonomous member organizations. Table 7 summarizes the empirical evidence for each meta-organizational role.

autonomous member organizations. Its Articles of Association establish governing bodies and collectively agreed rules, while thematic working groups, stakeholder forums and collaborative initiatives provide mechanisms through which members participate in and coordinate collective activities. These arrangements are consistent with the meta-organizational form in which autonomous

Table 7

**Observed meta-organizational roles performed by HUBA**

| Meta-organizational role | Main empirical evidence | Representative organizational activities |
|---|---|---|
| Governance and co-management | Articles of Association; working groups; quarterly reports; member meetings | Coordinating autonomous members; facilitating working groups; convening the General Assembly; organizing stakeholder forums |
| Advocacy | AFIR position paper; ACER consultation; regulatory consultations; interviews | Consolidating member views; policy dialogue; legislative consultation; representing members before authorities |
| Boundary and category work | Articles of Association; membership criteria; Competence Map; Battery Strategy 2030; media interviews | Defining organizational membership; mapping the battery ecosystem; promoting ecosystem legitimacy; strategic ecosystem development; public communication |
| Service provision | Emails; workshops; LinkedIn posts; Competence Map; Home Energy Storage Platform; professional book | Providing newsletters and technical information; training; conferences; comparison tools; knowledge services |

*Source: authors' synthesis*

*Service provision* was evident in HUBA's conferences, workshops, newsletters, technical publications, competence-development activities, study visits and digital platforms such as the Home Energy Storage Platform. These activities provided members with information, knowledge-sharing opportunities and other collective resources, consistent with Berkowitz et al.'s (2022) conceptualization of service provision as encompassing information production, research, training, knowledge sharing, capacity building and the provision of joint resources to members.

*Boundary and category work* was evident in HUBA's efforts to define the boundaries, identity and legitimacy of the emerging Hungarian battery ecosystem. Membership criteria contributed to defining which organizations could belong to the Association, while the Competence Map identified and categorized actors and capabilities within the battery ecosystem. HUBA's involvement in Battery Industry Strategy 2030 and its public communication further contributed to shaping the sector's strategic direction and collective identity. Media interviews addressing public concerns surrounding battery production, including the Samsung SDI case in Göd, also illustrate HUBA's engagement in strengthening the legitimacy and collective reputation of the sector. These activities are consistent with the boundary and category work of meta-organizations (Berkowitz et al., 2022), while the prominence of membership criteria also reflects the central importance of membership boundaries in meta-organizational forms (Ahrne et al., 2016).

*Governance and co-management* were evident in HUBA's formal decision-making arrangements and mechanisms for coordinating collective action among member organizations retain their organizational identities while participating in joint decision-making and collectively established governance arrangements (Ahrne et al., 2016).

*Advocacy* was evident in HUBA's representation of members' collective interests in national and European policy consultations. For example, in its response concerning the Alternative Fuels Infrastructure Regulation (AFIR), HUBA's position paper stated that it *"responds to the provisions of the Decree on the Development of Alternative Fuels Infrastructure... the opinions of other HU-BA members are also displayed."* This illustrates the meta-organizational character of HUBA's advocacy, whereby member positions were consolidated and represented collectively in the regulatory process consistent with the collective-interest representation associated with industry meta-organizations (Berkowitz et al., 2022).

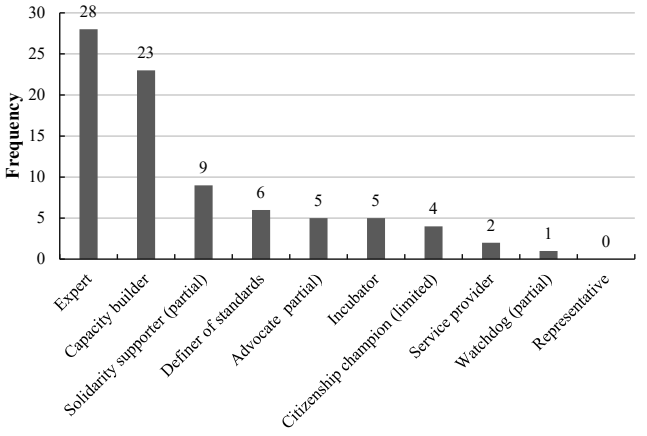
The findings therefore support the characterization of HUBA as meta-organizations that simultaneously facilitate interaction among members, undertake collective action towards their environment, construct collective identities and undertake common tasks on behalf of their members (Ahrne & Brunsson, 2008; Berkowitz et al., 2022).

## HUBA's role configuration from the civil society organization perspective

From the civil society organization perspective, we find that HUBA exhibited a selective role configuration (Figure 3). Expert (28 occurrences) and capacity builder (23) were the most frequently identified roles, while representative was not identified and watchdog and citizenship champion were only weakly evident.

Figure 3

**Civil society role profile of HUBA**




*Note: "Partial" or "limited" means there is some correspondence, but the activity does not fully satisfy WEF's definition.*
*Source: authors' analysis*

The role frequency distribution indicates that HUBA's most prominent CSO-type activities concern the provision of expertise and development of capabilities, whereas roles more directly associated with public accountability, citizen engagement and representation of under-represented groups are considerably less prominent (Table 8).

The *expert* role was the most prominent CSO function identified. It was reflected in HUBA's technical publications, professional conferences, regulatory and technological workshops, research-related activities and dissemination of specialist knowledge. The *capacity builder* role was similarly prominent and was evident in Battery Industry Basics lectures, workshops, study visits, laboratory facilities and other educational and knowledge-sharing activities aimed at strengthening the capabilities of members and other battery-ecosystem participants. These findings closely correspond to the WEF (2013) conception of CSOs as experts that contribute knowledge and experience to policy, strategy and solution development and as capacity builders providing education, training and capability development.

The *solidarity supporter* role was less prominent. Relevant activities included environmental protection and industrial safety initiatives, communication on responsible battery production and activities concerning recycling and circularity. Similarly, the *definer of standards* role was evident where HUBA contributed to the development or shaping of regulatory, technical and professional norms affecting the battery sector. Examples include HUBA's participation in consultations concerning alternative-fuels infrastructure, PFAS restrictions, battery carbon-footprint requirements and fire-safety rules.

The a*dvocate* role provides one of the clearest distinctions between the civil society and meta-organizational perspectives. Although HUBA actively participated in policy consultations and regulatory dialogue, these activities primarily represented the collective interests of member organizations and the battery sector and therefore corresponds more closely to meta-organizational advocacy

Table 8

**Observed civil society organization roles performed by HUBA**

| CSO role | Main empirical evidence | Interpretation |
|---|---|---|
| Expert | Technical publications; conferences; Battery Week; professional book; regulatory and technical workshops | HUBA produces and disseminates specialist knowledge and expertise |
| Capacity builder | Workshops; Battery Industry Basics lectures; study visits; laboratory facilities; training and knowledge platforms | HUBA develops capabilities among members and other ecosystem participants |
| Solidarity supporter | Sustainability-related events; environmental protection and safety activities; recycling and circularity initiatives | HUBA partially promotes broader values related to sustainability, safety and environmental responsibility |
| Definer of standards | Regulatory consultations; AFIR; PFAS; carbon-footprint and fire-safety discussions; professional benchmarks | HUBA contributes to shaping regulatory, technical and professional norms |
| Advocate | Regulatory consultations; environmental and sustainability communication | Advocacy occasionally addresses broader societal or environmental concerns but remains predominantly sector-oriented |
| Incubator | EIPP; Korea–Hungary Battery Cooperation Center; Battery Laboratory Equipment Park; research and circularity initiatives | HUBA supports the development of longer-term technological and innovation solutions |
| Citizenship champion | Home Energy Storage activities; public energy-storage and environmental communication | Citizen-facing engagement is present but limited |
| Service provider | Home Energy Storage Program; household comparison platform | Some services address societal or household needs beyond HUBA's membership |
| Watchdog | Environmental and sustainability-related public communication | Limited evidence of independent accountability or oversight |
| Representative | No clear qualifying activity identified | No evidence of systematic representation of marginalized or under-represented groups |

*Source: authors' synthesis*

than CSO-type advocacy which focuses on broader societal or environmental concerns (WEF, 2013). This distinction illustrates how apparently similar activities may fulfil different organizational roles depending on their purpose and intended beneficiaries.

The *incubator* role was evident in a smaller number of activities supporting longer-term technological and innovation development, including the European Industrial Partnership Programme, Korea–Hungary Battery Cooperation Center, Battery Laboratory Equipment Park, and research and circularity initiatives. These activities correspond to the WEF (2013) conception of incubation as developing solutions that may require relatively long gestation or payback periods.

The remaining CSO roles were only weakly evident. Limited *service provider* activity was identified where HUBA's activities addressed needs extending beyond its membership, particularly through the Home Energy Storage Program and household-oriented comparison platform. Similarly, *citizenship champion* activities were limited to a small number of citizen-facing initiatives and public communications concerning energy storage, sustainability and environmental issues, with little evidence of systematic citizen participation, empowerment or rights-oriented engagement.

The *watchdog* role was particularly weak. Although HUBA communicated on environmental regulation, sustainability and responsible battery production, little evidence was identified as independent monitoring, scrutiny or public accountability directed towards the battery industry or its members. There was also no clear evidence of the *representative* role as defined by WEF (2013), which concerns giving voice to marginalized or under-represented groups.

The findings indicate that HUBA's correspondence with the CSO framework is concentrated primarily in the *expert* and *capacity builder* roles, while roles associated with independent public accountability, citizen engagement and representation of marginalized or under-represented groups are weak or absent. Although HUBA is legally registered as a civil association in Hungary (HUBA, 2025), its observed CSO-type activities are predominantly oriented towards supporting members and the battery ecosystem, with more limited evidence of functions directed towards wider societal constituencies. This differentiated role configuration is consistent with the view that contemporary CSOs may perform multiple and overlapping roles, with their particular configuration varying according to organizational purpose and context (WEF, 2013; 2023).

## Explanatory contribution of industrial network management, meta-organization, and CSO perspectives to HUBA's role configuration

The preceding sections demonstrate that HUBA performs roles identified within industrial network management, meta-organization theory and civil society organization scholarship, although the explanatory reach of the three perspectives varies. A further finding is that many of the 58 identified organizational activities correspond to multiple roles across the theoretical perspectives. These overlaps do not indicate conceptual inconsistency; rather, the same activity may acquire different theoretical significance depending on its purpose, beneficiaries and relational context. Table 9 illustrates this cross-theoretical correspondence using selected HUBA activities.

Table 9

**Cross-theoretical interpretation of selected activities performed by HUBA**

| Organizational activity | Network management interpretation | Meta-organization interpretation | CSO interpretation |
|---|---|---|---|
| AFIR consultation | Goal setting and refining | Advocacy | Advocate (partial); definer of standards |
| Hungarian Battery Week / Battery Day | Coordinating; consolidating; leveraging; motivating | Governance and co-management; service provision; boundary and category work | Expert; capacity builder; solidarity supporter (partial) |
| HUBA Competence Map | Leveraging; coordinating | Boundary and category work; service provision | Expert; capacity builder |
| Home Energy Storage comparison platform | Leveraging; resourcing | Service provision | Expert; capacity builder; service provider; citizenship champion (limited) |
| EIPP / Korea–Hungary Battery Cooperation Center | Resourcing; leveraging; consolidating | Service provision; governance and co-management | Incubator; capacity builder; expert |
| Battery Laboratory Equipment Park | Resourcing; leveraging | Service provision | Expert; incubator; capacity builder |

*Source: authors' synthesis*

The three perspectives direct attention to different dimensions of the same organizational activities. At the same time, apparently similar roles across the perspectives are not necessarily conceptually equivalent. This is particularly evident in *advocacy* and *service provision*. HUBA's participation in regulatory consultations illustrates this distinction. From the meta-organization perspective, such activities constitute *advocacy* because the Association consolidates and represents the collective interests of its members. However, the same activity corresponds only partially to CSO advocacy because its primary purpose is the representation of member and sectoral interests rather

than advocacy concerning broader societal issues. The AFIR consultation also constitutes *goal setting and refining* from the industrial network management perspective because it contributes to shaping the regulatory environment affecting the network, and *definer of standards* from the CSO perspective through its contribution to regulatory development.

Similarly, Hungarian Battery Week and related professional events facilitate coordination, relationship building and knowledge exchange from the network-management perspective; provide collective services and mechanisms for member interaction from the meta-organization perspective; and perform primarily *expert* and *capacity builder* functions from the CSO perspective. While these activities constitute meta-organizational *service provision* because their principal beneficiaries are members and ecosystem participants, they do not necessarily correspond to the CSO *service provider* role, which requires a clearer orientation towards addressing societal needs. The purpose and intended beneficiaries of an activity are therefore important for distinguishing theoretically similar roles.

The HUBA Competence Map provides another illustration. By mapping organizations and capabilities across the Hungarian battery value chain, it facilitates *leveraging* and *coordination* among network actors. From the meta-organization perspective, it constitutes *service provision* and *boundary and category work* by providing a collective resource while identifying and categorizing actors within the battery ecosystem. From the CSO perspective, it primarily performs *expert* and *capacity builder* roles through the production of specialized knowledge and facilitation of access to complementary capabilities.

Our findings indicate that the three perspectives explain different but complementary dimensions of HUBA's role configuration. All roles identified by the industrial network management and meta-organization frameworks were evident in HUBA's activities, although their prevalence varied. In contrast, correspondence with the CSO framework was more selective, with some roles strongly evident and others weak or absent. The three perspectives therefore differ in their explanatory reach. Industrial network management captures HUBA's coordination of relationships and resources across the battery ecosystem, meta-organization theory captures its organization of collective member action, while the CSO perspective identifies the extent to which its activities extend towards broader societal functions. No single perspective fully explains HUBA's role configuration; the combined application of the three frameworks provides a more comprehensive understanding of the roles performed by industry associations in strategic industrial ecosystems.

## Conclusions and limitations

This study examined two research questions: what role configuration does the Hungarian Battery Association (HUBA) exhibit within Hungary's emerging battery ecosystem, and to what extent do industrial network management, meta-organization theory and civil society organization scholarship explain this configuration? To address these questions, the study adopted a qualitative single-case design and deductive thematic analysis of documentary evidence, complemented by interviews and participant observation for contextualization and triangulation.

Regarding the first research question, the findings reveal a multidimensional role configuration. All roles identified by the industrial network management and meta-organization frameworks were evident in HUBA's activities, although their prevalence varied. In contrast, correspondence with the CSO framework was more selective. Expert and capacity-builder functions were particularly prominent, whereas watchdog and citizenship-champion functions were weak, and no clear evidence was identified of the representative role as defined by WEF (2013).

Regarding the second research question, we find that no single theoretical perspective fully explains HUBA's role configuration. The industrial network management perspective captures HUBA's coordination of relationships, resources and interaction across the battery ecosystem, while meta-organization theory explains its collective governance, service provision, boundary and category work and representation of member interests. Civil society organization scholarship provides a complementary but more selective perspective by identifying the extent to which HUBA's activities extend towards broader societal functions. The three perspectives therefore differ in their explanatory reach but, when applied together, provide a more comprehensive understanding of the multidimensional roles performed by industry associations in strategic industrial ecosystems.

Our findings also reveal important conceptual distinctions between apparently similar roles. Advocacy provides a particularly clear example. Although advocacy appears in both meta-organization and CSO scholarship, HUBA's regulatory engagement predominantly reflects meta-organizational advocacy because it focuses on representing the collective interests of members and the battery sector, while corresponding only partially to the broader societal orientation of CSO advocacy. Similarly, HUBA's service provision was directed primarily towards members and ecosystem participants, consistent with the meta-organization perspective, and therefore differs conceptually from CSO service provision oriented towards wider societal needs. These findings demonstrate the importance of considering the purpose, beneficiaries and relational context of organizational activities rather than inferring organizational roles from activity labels alone.

The study consequently contributes to understanding industry associations in two related ways. First, it demonstrates empirically that the same organizational activity may simultaneously correspond to different theoretically defined roles. Activities such as policy consultations, conferences and knowledge platforms can simultaneously contribute to ecosystem coordination, collective member organization and selected societal functions depending on their purpose, beneficiaries and relational

context. Industrial network management, meta-organization theory and CSO scholarship should therefore be regarded as complementary rather than competing analytical perspectives. Second, the findings show that formal organizational status alone provides an incomplete basis for understanding industry associations. Although HUBA is legally registered as a civil association in Hungary, its observed activities correspond strongly to network-management and meta-organizational roles and more selectively to traditional CSO roles. A functional perspective therefore provides a more comprehensive understanding of industry associations than reliance on legal status or organizational labels alone.

The findings also suggest opportunities for extending research on meta-organizations. Recent scholarship proposes that differences among meta-organizations may be associated with how they acquire and deploy resources (Bor & Cropper, 2023). The present findings suggest that such differences may also be reflected in their role configurations. Future research could therefore examine whether and how resource availability and mobilization shape the relative emphasis placed on governance and co-management, advocacy, boundary and category work and service provision across different types of industry associations.

Several limitations should nevertheless be acknowledged. First, the single-case design and focus on one national industrial ecosystem limit the transferability of the findings to other organizational and institutional contexts. Second, the documentary analysis relied primarily on HUBA's official communications and therefore reflects activities made visible by the Association itself. Although interviews and participant observation provided supplementary evidence for contextualization and triangulation, the study did not systematically examine how external stakeholders perceive HUBA's roles, effectiveness or legitimacy. Third, the analysis identifies the roles performed by HUBA but does not evaluate the outcomes or effectiveness of those roles. Accordingly, the frequency with which a role was identified should not be interpreted as evidence of its effectiveness or impact.

Future research could address these limitations by comparing industry associations across national, regional and European levels and incorporating the perspectives of member and non-member firms, policymakers, civil society actors and local communities. Comparative studies could also examine whether particular role configurations generate different organizational or ecosystem outcomes.

Recent developments indicate that public controversy surrounding Hungary's battery industry has intensified, particularly concerning environmental impacts, foreign investment, regulatory oversight and community acceptance (Kronstein, 2026; Wu, 2024). These developments illustrate the dynamic institutional environment within which HUBA operates and suggest that longitudinal research could examine whether and how industry associations adapt their communication strategies and role configurations in response to changing societal expectations. In particular, future research could investigate whether growing societal scrutiny leads industry associations to assume more prominent citizen-facing, accountability or broader societal roles. As governments increasingly rely on intermediary organizations to coordinate industrial and sustainability transitions, understanding how these organizations balance member representation, ecosystem governance and broader societal expectations is likely to become increasingly important for both research and practice.

This study demonstrates that industry associations in strategic industrial ecosystems cannot be adequately understood through a single organizational lens. Their activities simultaneously involve coordinating ecosystem relationships, organizing collective member action and, to varying degrees, performing broader societal functions. Recognizing these multiple dimensions provides a more precise basis for understanding how industry associations contribute to the governance and development of emerging strategic industrial ecosystems.

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LÁSZLÓ BALÁZS

# PSYCHOLOGICAL MICROFOUNDATIONS OF ORGANIZATIONAL RELIABILITY IN SAFETY-CRITICAL INDUSTRIAL ENVIRONMENTS – EMOTIONAL INTELLIGENCE, SENSE OF COHERENCE, AND RESILIENCE AMONG EXPERIENCED INDUSTRIAL WORKERS

# A SZERVEZETI MEGBÍZHATÓSÁG PSZICHOLÓGIAI MIKROALAPJAI BIZTONSÁGKRITIKUS IPARI KÖRNYEZETEKBEN – ÉRZELMI INTELLIGENCIA, KOHERENCIAÉRZÉS ÉS REZILIENCIA TAPASZTALT IPARI MUNKAVÁLLALÓK KÖRÉBEN

The current study explores the psychological microfactors underlying resilience within safety-sensitive industries, with emphasis on the interplay between emotional intelligence, sense of coherence, and adaptability. In this respect, a conceptual model for the analysis of emotional intelligence, sense of coherence, and resilience was applied to an industrial sample of 460 employees, with 294 listwise valid cases. The findings revealed that self-regulatory emotional intelligence emerged as the best predictor of resilience (ß = .450, p < .001), whereas sense of coherence exhibited a partial mediation effect (ß = .171, p = .002). The explanatory strength of the mediation model was rather high ($R^2$ = .507). Moreover, emotional intelligence significantly predicted sense of coherence, especially self-regulatory (ß = .489, p < .001). The comparison between managers and subordinates demonstrated structural invariance; nevertheless, the relative significance of intrapersonal self-regulation proved to be more pronounced for managers, whereas sense of coherence had greater significance for followers.

Keywords: **emotional intelligence, resilience, sense of coherence, organizational reliability, safety-critical industrial environment**

A tanulmány a reziliencia pszichológiai mikrotényezőit vizsgálja biztonságkritikus ipari környezetben, különös tekintettel az érzelmi intelligencia, a koherenciaérzés és az adaptív működés kapcsolatára. A kutatás 460 fős ipari mintán, 294 listwise érvényes eset elemzésével tesztelte az érzelmi intelligencia, a koherenciaérzés és a reziliencia integrált modelljét. Az eredmények szerint az önszabályozó érzelmi intelligencia bizonyult a reziliencia legerősebb prediktorának (ß = .450, p < .001), míg a koherenciaérzés szignifikáns, részleges mediáló szerepet töltött be (ß = .171, p = .002). A mediációs modell magyarázóereje magas volt ($R^2$ = .507). Az érzelmi intelligencia a koherenciaérzést is jelentősen előre jelezte, különösen az önszabályozó dimenzió (ß = .489, p < .001). A vezetői és beosztotti csoportok összehasonlítása strukturális invarianciát mutatott, ugyanakkor a vezetők esetében az intraperszonális önszabályozás, míg a követőknél a koherenciaérzés relatív szerepe bizonyult hangsúlyosabbnak. Az eredmények alátámasztják, hogy a szervezeti megbízhatóság és az operatív stabilitás részben az egyéni pszichológiai szabályozási folyamatokra épül.

Kulcsszavak: **érzelmi intelligencia, reziliencia, koherenciaérzés, szervezeti megbízhatóság, biztonságkritikus ipari környezet**

**Funding/Finanszírozás:**
The author did not receive any grant or institutional support in relation with the preparation of the study.
A szerző a tanulmány elkészítésével összefüggésben nem részesült pályázati vagy intézményi támogatásban.

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The article was received: 17. 03. 2026, revised: 26. 05. 2026 and 02. 06. 2026, accepted: 02. 06. 2026.
A cikk beérkezett: 2026. 03. 17-én, javítva: 2026. 05. 26-án és 2026. 06. 02-án, elfogadva: 2026. 06. 02-án.

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Heavy industry, mechanical engineering, and automotive production systems represent complex sociotechnical environments in which safety and reliable operation cannot be explained solely by technological reliability. Analyses of accidents consistently show that failures rarely arise from isolated individual errors but from interactions between human decisions and organizational conditions. This perspective has led to the conceptualization of safety culture as the interplay between organizational structures and individual decision processes.

High Reliability Organization (HRO) research conceptualizes reliability as a collective capability based on continuous vigilance, sensitivity to failure, and decentralized expertise (Weick & Sutcliffe, 2007). Resilience engineering extends this perspective by framing performance as the capacity to anticipate, monitor, respond to, and learn from disturbances (Hollnagel et al., 2006; Hollnagel, 2015). Although these approaches emphasize organizational processes, they implicitly rely on individual psychological capacities that support stable performance under uncertainty.

At the individual level, resilience refers to adaptive functioning under stress and is increasingly conceptualized as a dynamic process emerging from interactions between psychological resources and environmental conditions (Connor & Davidson, 2003; Ungar, 2021). Within Antonovsky's (1987) salutogenic framework, sense of coherence–the perception of the environment as comprehensible, manageable, and meaningful–facilitates effective stress regulation. Empirical research confirms its association with psychological well-being, adaptive coping, and long-term health outcomes (Dziuba et al., 2021; Mittelmark et al., 2022).

In high-risk organizational environments, resilience therefore reflects both an individual psychological resource and a component of organizational adaptation. Previous research indicates that emotional intelligence can function as a protective factor against psychological strain and support resilient forms of organizational functioning (Balázs, 2020). Emotional intelligence may contribute to coherent situation appraisal, thereby increasing the likelihood of resilient functioning.

From this perspective, organizational stability does not imply error-free operation but the capacity to maintain core operational functions and decision quality under uncertainty. While resilience refers to adaptive capacity, organizational stability represents its functional outcome in the continuity of safety-critical performance (Hollnagel, 2014; Patriarca et al., 2018; Woods, 2015). However, existing resilience research primarily emphasizes structural and technological conditions and rarely operationalizes their psychological microfoundations (Hollnagel et al., 2006; Reason, 1997).

## Theoretical background

### Conceptual approaches to emotional intelligence and its organizational interpretation

Emotional intelligence (EI) is one of the most widely discussed psychological constructs in organizational behavior and leadership research because it links cognitive decision-making processes with emotional self-regulation. Classically, EI is defined as the ability to perceive, understand, and regulate emotions in ways that facilitate adaptive functioning and intellectual growth (Salovey & Mayer, 1990; Mayer, Salovey, & Caruso, 2008).

The literature distinguishes between ability-based and trait-based models of emotional intelligence. Ability models conceptualize EI as a form of emotional information processing comparable to cognitive intelligence, whereas trait models assess typical emotional self-perceptions and behavioral tendencies through self-report measures. In addition, mixed models integrate emotional competencies with broader personality characteristics and are frequently applied in organizational research (O'Boyle, Humphrey, Pollack, Hawver, & Story, 2011; Petrides, 2010).

The organizational relevance of emotional intelligence derives from the fact that emotions influence not only well-being but also decision-making and behavioral regulation. Meta-analytic evidence demonstrates a consistent relationship between emotional intelligence and job performance (Miao, Humphrey, & Qian, 2017). The cascade model proposed by Joseph and Newman (2010) further suggests that emotion perception and understanding influence performance primarily through emotion regulation processes.

In high-risk industrial environments, emotional intelligence becomes particularly relevant because stress, cognitive overload, and affective states can influence safety behavior and rule compliance (Clarke, 2010). Emotional self-regulation therefore plays a critical role in contexts characterized by technological complexity and high responsibility. From an organizational perspective, emotional intelligence can thus be interpreted as a psychological resource that supports cognitive control, stable decision-making, and adaptive responses to operational disturbances.

From the perspective of high-reliability organizational theory, emotional intelligence constitutes a psychological precondition for the individual-level enactment of reliability-enhancing behaviors. Weick and Sutcliffe (2007) identify mindful organizing – characterized by sensitivity to anomalies, reluctance to simplify, and deference to expertise – as the behavioral hallmark of high-reliability performance. Each of these behaviors requires the kind of attentional stability and regulatory control that emotional intelligence supports: without effective management of affective states, perceptual sensitivity degrades, cognitive simplification increases, and

interpersonal deference breaks down. Emotional intelligence in safety-critical industrial contexts can therefore be understood not merely as a performance resource but as a functional prerequisite for the psychological processes underlying organizational reliability.

## Definition of resilience and its relationship with emotional intelligence

Resilience is commonly defined as adaptive functioning under conditions of stress or adversity (Masten, 2001). Contemporary perspectives conceptualize resilience as a dynamic regulatory process involving situation appraisal, self-regulation, and the mobilization of psychological resources (Bonanno, 2004; Kalisch et al., 2015; Luthar, Cicchetti, & Becker, 2000; Ungar, 2021).

In organizational contexts, resilience has both an individual and a collective dimension. At the individual level it refers to the capacity for flexible adaptation to stress, while at the collective level it forms a microfoundation of team and organizational resilience (Lengnick-Hall, Beck, & Lengnick-Hall, 2011; Williams, Gruber, Sutcliffe, Shepherd, & Zhao, 2017). From this perspective, organizational resilience emerges from aggregated patterns of individual adaptive functioning, which is particularly relevant in high-risk industrial environments where operational stability depends heavily on the quality of individual decisions and responses (Vogus & Sutcliffe, 2007).

Recent research emphasizes that resilient adaptation is grounded in psychological regulatory processes, particularly emotion regulation and cognitive control (Bonanno & Burton, 2013). Flexible regulation of negative affect and cognitive reappraisal of stressful situations reduce dysfunctional stress responses and facilitate adaptive coping (Southwick & Charney, 2012).

Empirical studies demonstrate that intrapersonal EI components–such as self-awareness and self-control–are significant predictors of psychological resilience in the context of stress and adversity (Armstrong, Galligan, & Critchley, 2011). Further research indicates that emotional intelligence contributes to the flexible use of emotion regulation strategies, which represent a core mechanism of resilient adaptation (Double, Pinkus, & MacCann, 2022; Schneider, Lyons, & Khazon, 2013).

The organizational interpretation of resilience is also consistent with resilience engineering, which conceptualizes system stability through the capacities to anticipate, monitor, respond, and learn from disturbances (Hollnagel, 2014). Although formulated primarily at the system level, these capacities rely on individual psychological resources such as emotional self-regulation and cognitive control. In technologically complex and safety-critical work environments, these psychological resources play a crucial role in maintaining operational stability and enabling recovery from unexpected disruptions (Beus, Payne, Bergman, & Arthur, 2010; Clarke, 2010). This connection between individual psychological resilience and system-level reliability is particularly consequential in safety-critical industrial environments. Hollnagel's (2014) four resilience capacities – the ability to anticipate potential disruptions, monitor developing situations, respond to disturbances, and learn from experience – each presuppose individual psychological resources that enable stable cognitive and regulatory functioning under pressure. Anticipation requires the cognitive capacity to hold multiple scenarios simultaneously without affective overload; monitoring requires sustained attentional control; response requires rapid and flexible behavioral regulation; and learning requires the capacity to reflect on experience without defensive distortion. Individual resilience, operationalized as adaptive functioning under stress, can therefore be understood as the psychological substrate that makes these system-level capacities individually enactable. The present study's focus on safety-critical industrial workers thus moves beyond the general organizational literature by testing this model in a population where the relationship between individual psychological resources and system reliability carries direct operational and safety implications.

## Sense of coherence and salutogenesis: organizational applications and mediating mechanisms

Antonovsky's salutogenic theory introduced the concept of sense of coherence (SOC), defined as the extent to which individuals perceive their environment as comprehensible, manageable, and meaningful (Antonovsky, 1987). SOC reflects a generalized orientation through which individuals interpret situations as structured and controllable, facilitating effective coping with environmental demands.

Empirical research provides strong support for the protective role of SOC in stressful contexts. A systematic review by Eriksson and Lindström (2006), synthesizing several hundred studies, demonstrated consistent positive associations between SOC and both mental and physical health outcomes. Subsequent meta-analytical findings further confirmed this protective function; for example, Schäfer et al. (2019) reported a substantial negative correlation between SOC and posttraumatic stress symptoms ($r \approx -0.41$).

In organizational research, SOC has increasingly been examined as a mechanism linking workplace conditions and employee well-being. Studies show that SOC can mediate the relationship between psychosocial job demands and psychological outcomes (Feldt, Kinnunen, & Mauno, 2000). Building on this perspective, the concept of work-specific sense of coherence (Work-SOC) was developed to capture comprehensibility, manageability, and meaningfulness within the work environment. Vogt et al. (2013) validated the Work-SOC scale, and subsequent longitudinal research demonstrated that workplace resources can predict increases in SOC and thereby enhance work engagement (Vogt et al., 2016). In safety-critical industrial contexts, the three components of SOC acquire specific operational meaning that extends their general psychological function. Comprehensibility – the sense that one's environment is structured and predictable – maps onto the operator's capacity to maintain an accurate situational model of complex technical

systems; its degradation under stress is a recognized precursor to accidents and near-misses (Reason, 1997). Manageability – the perception that one possesses sufficient resources to meet demands – corresponds to the operator's sense of task efficacy under time pressure and high responsibility. Meaningfulness – the experience of work as worthy of engagement and effort – supports sustained motivational commitment to safe performance even in routine, repetitive operational conditions. In this context, sense of coherence functions not merely as a general well-being resource but as a psychological stabilizer of the interpretive processes that underlie reliable human performance in safety-critical systems. This reframing positions SOC as a theoretically novel construct within the resilience engineering literature, where equivalent concepts have been articulated at the system level – such as Hollnagel's (2014) notion of functional readiness – but never operationalized at the level of individual psychological experience.

The relationship between emotional intelligence and sense of coherence can be explicated through a three-stage cognitive–affective regulatory process. In the first stage, emotional self-regulation – particularly impulse control and stress tolerance – functions as an affective filter: by preventing the cognitive system from being overwhelmed by negative emotional states, it preserves cognitive resources by modulating the affective response before it disrupts structured information processing – consistent with Gross's (2002) process model of emotion regulation (Côté, 2014). In the second stage, this reduction in affective load creates the cognitive conditions under which work situations can be appraised as comprehensible, manageable, and meaningful – the three defining components of sense of coherence (Antonovsky, 1987). Importantly, emotional intelligence does not directly produce coherence; rather, it removes the affective obstacles that would otherwise distort coherent situational appraisal. In the third stage, this coherent interpretive orientation stabilizes the individual's representation of the work environment, reduces subjective uncertainty – itself a primary stressor in operationally demanding contexts – and thereby preserves the cognitive resources required for flexible, adaptive responding. In high-risk industrial environments, this freed cognitive capacity constitutes a foundational condition for resilient functioning: it supports anticipation of disturbances, stable decision-making under time pressure, and recovery from unexpected operational disruptions (Hollnagel, 2014; Kalisch, Müller, & Tüscher, 2015).

## Research objectives and hypotheses

The present study examines how individual psychological resources contribute to operational stability and organizational reliability in high-risk industrial environments. It builds on the assumption that organizational resilience is not solely a structural or procedural characteristic but is partly realized through individual regulatory and interpretive mechanisms.

Specifically, the study investigates the relationships among emotional intelligence, sense of coherence, and resilience. Emotional intelligence is assumed to support resilient functioning, while sense of coherence may function as a mediating mechanism linking emotional competencies to adaptive responses. Within this framework, sense of coherence is conceptualized as an interpretative orientation that structures how individuals perceive and manage complex work environments.

The present study is primarily confirmatory in nature: its hypotheses build on theoretically well-established and empirically supported relationships, and the study's central aim is to test whether these relationships replicate within a specific and underrepresented population – namely, experienced employees in heavy industry, mechanical engineering, and the automotive sector. At the same time, the study extends prior work in three respects: it integrates emotional intelligence, sense of coherence, and resilience within a single structural model that has not been tested in this combination; it applies this model in a Central European industrial context where cross-cultural generalizability cannot be assumed; and it examines whether the relative weighting of psychological resources varies across hierarchical roles – a comparison that retains an exploratory dimension.

The theoretical argument also draws on Conservation of Resources (COR) theory, which posits that stress emerges when individuals experience resource loss or perceive a threat to valued resources (Hobfoll, 1989). Within this perspective, emotional intelligence and sense of coherence can be interpreted as personal resources that help maintain stable functioning under demanding conditions. Emotional intelligence, particularly through emotion regulation processes, supports cognitive control and consistent decision-making. Meta-analytic evidence indicates that emotion regulation plays a central role in the relationship between emotional intelligence and performance outcomes (Joseph & Newman, 2010), and empirical findings demonstrate significant associations between intrapersonal EI components and psychological resilience (Armstrong et al., 2011). Accordingly, the following hypothesis is proposed:

*H1. Emotional intelligence is positively related to resilience.*

A distinctive feature of sense of coherence is that it represents not only a coping resource, but also an interpretive framework: it structures the perception of the work environment and shapes the representation of stressors. Research on Work-SOC has demonstrated that the perceived comprehensibility and manageability of the work environment are associated with employee well-being and work engagement (Vogt et al., 2016). From a theoretical perspective, emotional self-regulation may contribute to more coherent situation perception by reducing affective "noise" and stabilizing the sense of control (Côté, 2014). Based on this logic:

*H2. Emotional intelligence is positively related to individual sense of coherence.*

The mediation logic underlying the proposed model is based on the assumption that personal resources build upon one another. According to the JD–R model, personal resources may function as mediators between environmental factors and outcomes (Xanthopoulou et al., 2007). Sense of coherence is supported by a substantial evidence base linking it to favorable mental health outcomes (Eriksson & Lindström, 2006), and it has also been identified as a mediating mechanism in workplace studies (Feldt et al., 2000). On this basis, it can be assumed that the effect of emotional intelligence is partially transmitted through the coherent experience of the work environment.

*H3. Sense of coherence partially mediates the relationship between emotional intelligence and resilience.*

With regard to the dimensionality of emotional intelligence, prior empirical findings suggest that intrapersonal, self-regulatory components are more strongly associated with resilience than interpersonal dimensions (Armstrong et al., 2011). In the context of organizational performance outcomes, emotion regulation has also been identified as the strongest link within the cascade model (Joseph & Newman, 2010). In high-risk industrial environments–where attentional stability and control under stress are particularly critical–the examination of the dominant role of self-regulatory components is therefore especially warranted.

*H4. The self-regulatory component of emotional intelligence predicts resilience more strongly than social–adaptive components.*

Finally, the potential moderating role of organizational position can be theoretically derived from role theory and the logic of the JD–R model (Bakker & Demerouti, 2017). Leadership roles may simultaneously entail greater resources (e.g., autonomy, decision authority) and greater demands (e.g., responsibility, emotional labor). Meta-analytic findings indicate that the relationship between emotional intelligence and workplace outcomes is context-dependent and tends to be particularly strong in leadership roles and in positions characterized by high emotional demands (Harms & Credé, 2010; Miao, Humphrey, & Qian, 2017). This justifies examining whether the proposed pattern of relationships is structurally generalizable and whether the relative importance of psychological resources differs across hierarchical levels within the organization.

*H5. Leader and follower roles do not alter the psychological core mechanisms underlying resilience; however, the relative importance of associated psychological resources differs across hierarchical levels within the organization.*

Figure 1 summarizes the hypothesized relationships among the study variables.

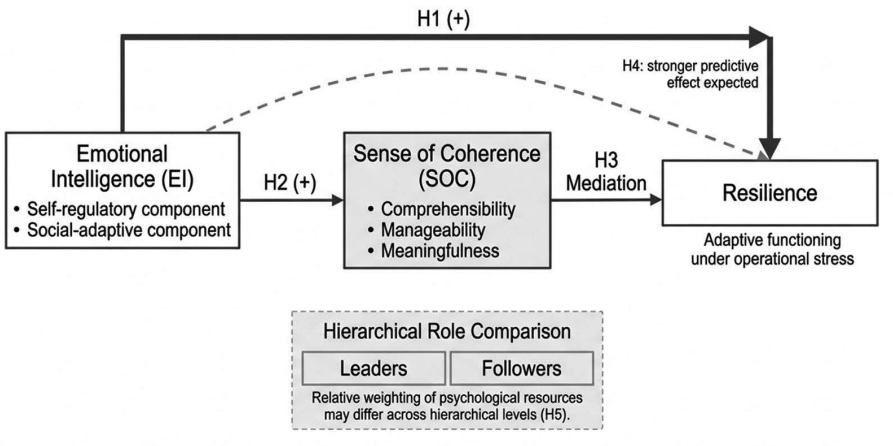
## Methodology

### Sample

The empirical data collection was conducted in collaboration with four Hungarian trade union organizations whose membership is predominantly employed in operationally demanding and safety-critical industrial sectors: the Vasutasok Szakszervezete (Railway Workers' Union), the Mozdonyvezetők Szakszervezete (Train Drivers' Union), the Vasúti Dolgozók Szabad Szakszervezete Szolidaritás (Free Union of Railway Employees – Solidarity), and the Munkástanácsok Országos Szövetsége (National Federation of Workers' Councils), the latter representing

Figure 1

**Conceptual model of the hypothesized relationships among emotional intelligence, sense of coherence, and resilience in safety-critical industrial environments**




*Source: own compilation*

employees across heavy industry, mechanical engineering, and the automotive sector. Railway operations in particular constitute a paradigmatic high-reliability organizational context, characterized by technological complexity, real-time decision-making under time pressure, and consequential safety demands (Weick & Sutcliffe, 2007). The study therefore targeted an active industrial workforce population embedded in organizational environments where operational reliability and individual regulatory capacity carry direct functional significance.

Data were collected with the assistance of trained interviewers who personally contacted participants, informed them about the purpose of the study, and ensured standardized administration of the questionnaire. Their role was limited to providing information and technical assistance; they did not influence the content of the responses.

The data analysed in the present study were collected within the framework of the GINOP-5.3.5-18 European Social Fund project (project identifiers: GINOP-5.3.5-18-2018-00052 and GINOP-5.3.5-18-2018-00053), implemented in cooperation with the participating trade union organizations. The author contributed to the project as a co-investigator, and the subsequent use of the collected data for independent scientific purposes was authorized by the project leader and a representative of the participating trade union federation. Throughout data collection, participants' rights were fully protected: participation was voluntary, respondents were informed about the purpose of the research prior to completing the questionnaire, anonymity and confidentiality were guaranteed, and no personally identifiable information was recorded or retained. All data were handled in accordance with applicable data protection regulations.

The total sample size was N = 460, while the number of listwise valid cases used in the regression and mediation analyses was 294. The sample included both leaders and non-leaders, enabling comparative analyses across organizational roles.

The mean age of participants was 44.78 years (SD = 11.84), with ages ranging from 19 to 77 years. The gender composition of the sample was 70.2% male (n = 320) and 29.8% female (n = 136), reflecting the male-dominated character of the heavy industrial and railway sectors from which the sample was drawn. Average total work experience was 23.90 years (SD = 12.83), and mean tenure in the current position was 11.88 years (SD = 10.24). The survey did not include a systematic assessment of occupational roles or educational background; this represents a limitation of the present study and is acknowledged as such in the Limitations section. Overall, the sample consisted predominantly of experienced industrial employees with long-term organizational embeddedness, providing a suitable context for examining operational stability and resilience.

## Emotional intelligence – Bar-On model

Emotional intelligence was measured using a Hungarian-language translation of the Bar-On Emotional Quotient Inventory (EQ-i; Bar-On, 1997, 2006). While a formally published and independently standardized Hungarian validation of the full adult EQ-i has not been established in the peer-reviewed literature, the instrument has been applied in Hungarian academic and organizational research contexts, including doctoral dissertations (Balázs, 2014; Kun, 2011; Majoros, 2008), providing a precedent for its use with Hungarian-speaking samples. In the present study, psychometric adequacy was evaluated within the sample: internal consistency of the full scale proved satisfactory (Cronbach's $\alpha > .80$), corrected item–total correlations exceeded accepted thresholds for all items, and the factor structure was examined empirically rather than assumed on the basis of the original normative model. The model conceptualizes emotional intelligence as a multidimensional "mixed" construct integrating intrapersonal and interpersonal competencies, adaptability, stress management, and general mood. This framework is widely used in organizational research because it captures functional emotional competencies–such as emotion regulation, problem solving, impulse control, and optimism–that are directly related to workplace adaptation (Bar-On, 2006).

The selection of the Bar-On mixed model over alternative conceptualizations of emotional intelligence was guided by three considerations specific to the present research context. Ability-based models (Mayer, Salovey, & Caruso, 2008) conceptualize EI as a form of emotional information processing and require performance-based administration conditions that are difficult to standardize in large-scale field settings with heterogeneous workforce samples. Trait-based models (Petrides, 2010), while suitable for self-report administration, primarily capture stable emotional dispositions rather than the functional competencies most relevant to workplace adaptation. The Bar-On mixed model, by contrast, operationalizes EI through competencies with direct organizational relevance – including impulse control, stress tolerance, and problem-solving under pressure – that have particular face validity in safety-critical industrial environments where regulatory and adaptive demands are high (Clarke, 2010). Additionally, the Bar-On framework has been extensively applied in organizational research, providing a broad comparative base for contextualizing the present findings (O'Boyle et al., 2011). These considerations do not preclude the value of ability-based assessments, and future research comparing model types in industrial samples would constitute a meaningful extension of the present work.

Previous research indicates that the dimensional structure of mixed emotional intelligence models may vary across samples (Joseph & Newman, 2010). Accordingly, the factor structure of the scale was empirically examined in the present industrial sample rather than assuming the original five-factor structure a priori.

## Psychometric foundations of the emotional intelligence measurement model

The internal consistency of the full EI scale proved to be satisfactory (Cronbach's $\alpha > .80$). To examine the dimensional structure of emotional intelligence, Principal Axis Factoring with Varimax rotation was applied. The sample

proved suitable for factor analysis, as indicated by an excellent Kaiser–Meyer–Olkin value (KMO > .90) and a significant Bartlett's test of sphericity ($p < .001$). Based on the eigenvalue > 1 criterion and inspection of the scree plot, two stable factors were identified. The first factor reflected adaptive–social functioning, whereas the second represented self-regulation, stress management, and impulse control. The correlation between the factors was moderate ($r \approx .55$), and both showed satisfactory internal consistency (Cronbach's $\alpha > .75$).

The full scale showed high internal consistency (Cronbach's $\alpha > .80$), corrected item–total correlations exceeded the accepted threshold for all items ($r > .30$), and removal of individual items did not improve reliability. For subsequent analyses, standardized factor scores calculated using the regression method were applied. Regression results indicated that the self-regulatory factor showed stronger associations with sense of coherence ($\beta = .489$, $p < .001$) and resilience ($\beta = .450$, $p < .001$) than the adaptive–social factor, supporting the predictive validity of the empirically derived two-factor structure. Accordingly, subsequent structural analyses were based on this sample-specific two-factor EI model (Table 1).

Table 1

**Two-factor measurement model of emotional intelligence**
(Principal Axis Factoring, Varimax rotation)

| Item | Adaptive–Social EI | Self-Regulatory EI | $h^2$ |
|---|---|---|---|
| Social responsibility | .844 | – | .741 |
| Interpersonal relations | .766 | – | .687 |
| Empathy | .607 | – | .401 |
| Problem solving | .662 | – | .591 |
| Reality testing | .632 | – | .585 |
| Flexibility | .413 | – | .250 |
| Optimism | .548 | .484 | .535 |
| Happiness | .663 | .413 | .610 |
| Self-confidence | – | .756 | .605 |
| Independence | – | .735 | .564 |
| Stress tolerance | – | .688 | .530 |
| Impulse control | – | .527 | .280 |
| Self-esteem | .470 | .659 | .656 |
| Self-awareness | .589 | .581 | .684 |
| Self-actualization | .725 | .420 | .701 |

*Note. Only factor loadings with $|\lambda| \geq .40$ are reported.*
*Source: own compilation*

## Sense of coherence – Antonovsky's SOC Scale (Hungarian validation)

Sense of coherence was assessed using the shortened Sense of Coherence Scale (SOC-13), based on Antonovsky's (1987) salutogenic theory. The construct comprises three components: comprehensibility, manageability, and meaningfulness. The questionnaire consists of 13 items, which respondents rate on a 7-point Likert scale; total scores range from 13 to 91, with higher scores indicating a stronger sense of coherence.

In the present study, the Hungarian-language validated version of the scale was used. The psychometric properties of the Hungarian adaptation were examined by Balajti and colleagues (2007) in a heterogeneous societal sample ($N = 128$). The internal consistency of the scale proved to be satisfactory (Cronbach's $\alpha = .82$). Principal component analysis identified a three-factor structure, accounting for 56% of the total variance. Convergent and criterion validity of the construct were supported by significant associations in theoretically expected directions with measures of mental health, including the GHQ-12, the Beck Depression Inventory, and indicators of perceived health status. Test–retest reliability over a five-month interval demonstrated adequate temporal stability. Based on these validation results, the Hungarian version of the SOC-13 can be considered a reliable and valid measurement instrument suitable for empirical research conducted in organizational and workplace samples.

### *Resilience – 10-Item Connor–Davidson Resilience Scale (CD-RISC-10)*

Resilience was assessed using the Hungarian adaptation of the 10-item short version of the Connor–Davidson Resilience Scale (CD-RISC-10). The original CD-RISC was developed by Connor and Davidson (2003) as a 25-item instrument with a multidimensional structure. Subsequent studies, however, were unable to consistently replicate the original factor structure; therefore, Campbell-Sills and Stein (2007) developed a shortened, unidimensional 10-item version of the scale.

The Hungarian adaptation was carried out by Járai and colleagues (2015), who confirmed a stable, unidimensional structure using confirmatory factor analysis. Model fit indices indicated an acceptable fit: $\chi^2(35) = 40.047$; $\chi^2/df = 1.144$; CFI = .952; TLI = .926; RMSEA = .047.

The Cronbach's alpha coefficient of the scale was .85, corresponding to the reliability reported for the original short version. The Hungarian CD-RISC-10 validated by Járai et al. (2015) demonstrates adequate convergent and discriminant validity and is suitable for distinguishing between clinical and non-clinical populations. In the present study, resilience was treated as a unidimensional construct and operationalized using the total score.

## Analytical strategy

The analytical strategy consisted of several steps. First, descriptive statistics and bivariate correlations were calculated to examine associations among the study variables. Next, the dimensional structure of emotional intelligence was explored using exploratory factor analysis (Principal Axis Factoring with Varimax rotation). Sampling adequacy was assessed using the Kaiser–Meyer–Olkin measure and Bartlett's test of sphericity. Standardized factor scores were computed and used in subsequent analyses. Hypotheses were tested using multivariate linear regression models. Mediation effects were examined with a bootstrap-based procedure (PROCESS macro, Model 4), which allows robust estimation of indirect effects without assuming normality. Role differences (leader vs. follower)

were assessed using group-specific regression models and interaction-based moderation analyses.

## Results

### Correlation analysis

Correlation analyses indicated significant positive associations among the main variables. Both adaptive ($r \approx .56$, $p < .001$) and self-regulatory emotional intelligence ($r \approx .63$, $p < .001$) were moderately related to resilience. Emotional intelligence was also positively associated with sense of coherence (adaptive: $r \approx .56$; self-regulatory: $r \approx .65$; $p < .001$), while sense of coherence correlated with resilience ($r \approx .55$, $p < .001$), satisfying the statistical prerequisites for mediation analysis (Table 2).

Table 2

**Descriptive statistics and correlations of the main variables**

| *Variable* | *N* | *Min* | *Max* | *M* | *SD* | *1* | *2* | *3* | *4* |
|---|---|---|---|---|---|---|---|---|---|
| *1. Resilience* | 440 | 0 | 4 | 2.88 | 0.69 | – | | | |
| 2. Sense of coherence | 426 | 2 | 7 | 4.90 | 0.89 | .548** | – | | |
| 3. EI Adaptive | 334 | −2.51 | 2.15 | 0.00 | 0.97 | .564** | .565** | – | |
| 4. EI Self-regulatory | 334 | −2.61 | 2.77 | 0.00 | 0.93 | .627** | .649** | .629** | – |

*Note. Pearson correlations. **p < .01. Sample sizes vary by variable due to pairwise handling of missing data. Emotional intelligence dimensions are standardized factor scores (M = 0, SD ≈ 1).*

*Source: own compilation*

The observed pattern of associations confirmed that emotional intelligence was related both to the hypothesized mediator (sense of coherence) and to the outcome variable (resilience), and that the mediator was also significantly associated with resilience.

#### *The effect of emotional intelligence on resilience*

The direct relationship between emotional intelligence and resilience was examined using multivariate regression analysis. When resilience was entered as the dependent variable and the two emotional intelligence factors were included as predictors, both dimensions showed significant positive effects. The adaptive dimension predicted resilience ($B = 0.197$; $\beta = 0.279$; $p < .001$), while the self-regulatory dimension emerged as a stronger predictor ($B = 0.333$; $\beta = 0.450$; $p < .001$). In the mediation model including sense of coherence, SOC was a significant predictor of resilience ($B = 0.132$; $\beta = 0.171$; $p = .002$). The effects of emotional intelligence remained significant but decreased (adaptive: $\beta = 0.265$; $p < .001$; self-regulatory: $\beta = 0.377$; $p < .001$), indicating partial mediation (Table 3).

Bootstrap mediation analysis (PROCESS Model 4, 5,000 resamples) further confirmed the mediating role of sense of coherence. For the self-regulatory emotional intelligence dimension, the indirect effect was significant ($B = 0.110$; 95% CI [.048, .175]), while the direct effect remained significant ($B = 0.367$; $\beta = 0.510$; $p < .001$). For the adaptive dimension, the direct effect was also significant ($B = 0.299$; $\beta = 0.425$; $p < .001$), and the indirect effect through sense of coherence was significant ($B = 0.129$; 95% CI [.084, .181]).

#### *The effect of emotional intelligence on sense of coherence*

Correlation analyses indicated significant positive associations between emotional intelligence and sense of coherence (adaptive: $r \approx .56$; $p < .001$; self-regulatory: $r \approx .65$; $p < .001$).

A multivariate regression model was estimated with sense of coherence as the dependent variable and the two emotional intelligence dimensions as predictors. Both factors showed significant positive effects. The adaptive dimension predicted sense of coherence ($B = 0.223$; $\beta = 0.245$; $p < .001$), while the self-regulatory dimension emerged as a stronger predictor ($B = 0.456$; $\beta = 0.489$; $p < .001$) (Table 4).

Table 3

**Effects of emotional intelligence dimensions and sense of coherence on resilience**
(Multivariate linear regression – mediation control model)

| Predictor | B | SE | β | t | p | Tolerance | VIF |
|---|---|---|---|---|---|---|---|
| **EI – Adaptive dimension** | 0.187 | 0.039 | 0.265 | 4.848 | < .001 | 0.537 | 1.861 |
| **EI – Self-regulatory dimension** | 0.271 | 0.043 | 0.377 | 6.330 | < .001 | 0.454 | 2.201 |
| **Sense of coherence (SOC)** | 0.132 | 0.042 | 0.171 | 3.139 | .002 | 0.544 | 1.839 |

*Note. Dependent variable: resilience. $R = .712$; $R^2 = .507$; Adjusted $R^2 = .503$; $F(3, 306) = 105.07$, $p < .001$. Both emotional intelligence dimensions remained significant after inclusion of sense of coherence, while their standardized coefficients decreased relative to the baseline model. Sense of coherence emerged as an independent, significant predictor, indicating partial mediation in regression terms. Multicollinearity diagnostics (Tolerance > .45; VIF < 2.3) suggest adequate model stability.*

*Source: own compilation*

Table 4

**Effects of emotional intelligence dimensions on sense of coherence**
(Multivariate linear regression)

| Predictor | B | SE | β | t | p | Tolerance | VIF |
|---|---|---|---|---|---|---|---|
| EI – Adaptive dimension | 0.223 | 0.051 | 0.245 | 4.407 | < .001 | 0.571 | 1.752 |
| EI – Self-regulatory dimension | 0.456 | 0.052 | 0.489 | 8.804 | < .001 | 0.571 | 1.752 |

*Note. Dependent variable: sense of coherence. $R = .675$; $R^2 = .456$; Adjusted $R^2 = .452$; $F(2, 309) = 129.47$, $p < .001$. Both emotional intelligence dimensions are positively and significantly associated with sense of coherence. Based on standardized coefficients, the effect of the self-regulatory dimension is nearly twice that of the adaptive dimension. Multicollinearity diagnostics (Tolerance > .57; VIF < 1.8) indicate adequate model stability.*
*Source: own compilation*

## Differences by leadership and follower roles

To examine whether the structural relationships among emotional intelligence, sense of coherence, and resilience differ across hierarchical levels, the sample was divided into leaders (N = 84) and followers (N = 376).

Group-specific regression models were first estimated using split-file analyses. Subsequently, a formal moderation test was conducted using an interaction-based regression model to assess whether organizational role significantly altered the relationships among the examined variables.

### *Group-Specific Regression Models*

Separate regression models were estimated to predict resilience in the leader and follower subsamples. In the leader group, self-regulatory emotional intelligence emerged as the only significant and strong predictor of resilience (B = 0.304; β = 0.652; p < .001), whereas the effect of sense of coherence was not significant (B = −0.011; β = −0.023; p = .865). In contrast, within the follower subsample both self-regulatory emotional intelligence (B = 0.371; β = 0.488; p < .001) and sense of coherence (B = 0.211; β = 0.262; p < .001) emerged as significant and positive predictors (Table 5).

The group-specific models therefore delineate different emphases at a descriptive level: leader resilience appears to be predominantly intrapersonal in nature, whereas follower resilience is partly embedded in the organisational context.

### *Interaction (Moderation) Model*

To examine whether the psychological core mechanisms of resilience differ structurally between leader and follower groups, an interaction-based regression model was applied. Resilience was specified as the dependent variable, emotional intelligence dimensions and sense of coherence were entered as main effects, and organizational role (leader vs. follower) was included as a moderator. The interaction terms used were adaptive EI × role, self-regulatory EI × role, and sense of coherence × role.

None of these coefficients reached statistical significance, suggesting that organizational role does not have a major moderating effect on emotional intelligence or sense of coherence in their contribution to resilience: adaptive EI × role: p = .443; self-regulatory EI × role: p = .259; sense of coherence × role: p = .194. It can therefore be argued that the core elements of this model are statistically invariant across hierarchical levels. Multicollinearity

Table 5

**Effects of self-regulatory emotional intelligence and sense of coherence on resilience**
(Leader and follower subsamples; control regression analyses)

**Panel A. Follower subsample (Role = 0)**

| Predictor | B | SE | β | t | p | Tolerance | VIF |
|---|---|---|---|---|---|---|---|
| EI – Self-regulatory dimension | 0.371 | 0.046 | 0.488 | 8.079 | < .001 | 0.600 | 1.668 |
| Sense of coherence (SOC) | 0.211 | 0.049 | 0.262 | 4.334 | < .001 | 0.600 | 1.668 |

*Note (Panel A). Dependent variable: resilience. $R = .684$; $R^2 = .468$; Adjusted $R^2 = .464$; $F(2, 243) = 107.03$, $p < .001$. In the follower subsample, both self-regulatory emotional intelligence and sense of coherence emerged as significant, positive predictors.*

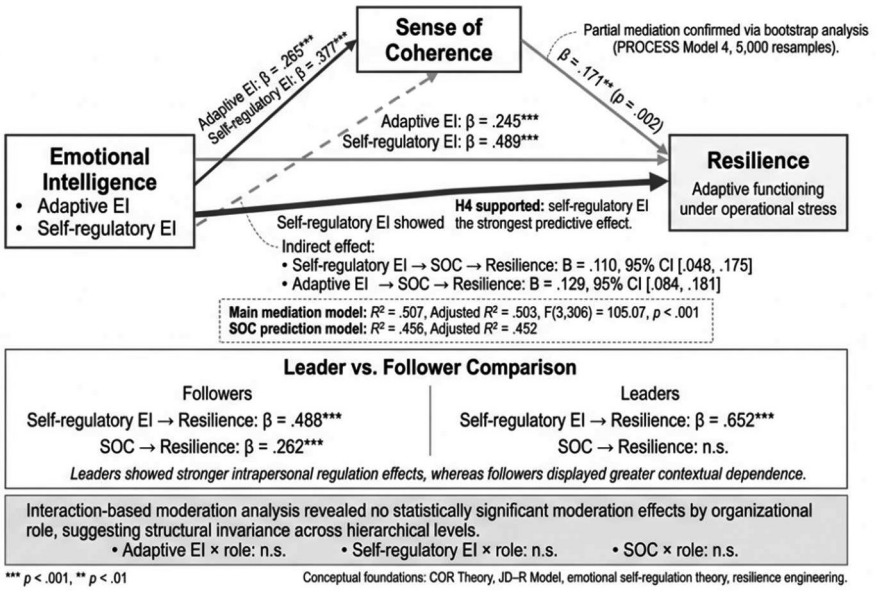
**Panel B. Leader subsample (Role = 1)**

| Predictor | B | SE | β | t | p | Tolerance | VIF |
|---|---|---|---|---|---|---|---|
| EI – Self-regulatory dimension | 0.304 | 0.061 | 0.652 | 4.944 | < .001 | 0.559 | 1.790 |
| Sense of coherence (SOC) | −0.011 | 0.065 | −0.023 | −0.171 | .865 | 0.559 | 1.790 |

*Note (Panel B). Dependent variable: resilience. $R = .638$; $R^2 = .407$; Adjusted $R^2 = .387$; $F(2, 61) = 20.90$, $p < .001$. In the leader subsample, only self-regulatory emotional intelligence emerged as a significant predictor, whereas the effect of sense of coherence was not significant.*
*Source: own compilation*

Figure 2

**Empirical mediation and role-comparison model of emotional intelligence, sense of coherence, and resilience. Integrated Interpretation of Role Differences**




*Source: own compilation*

diagnostics were also within acceptable limits (VIF = 1.6 to 2.5). Figure 2 presents the empirically supported path coefficients of the tested model.

Joint interpretation of the split-file analyses and the moderation model indicates that the structural relationships among emotional intelligence, sense of coherence, and resilience are largely similar across leader and follower groups. The interaction tests did not reveal significant moderation effects, suggesting that the underlying mechanisms operate according to the same structural logic in both groups.

At a descriptive level, however, differences emerged in the relative weighting of resources. In the leader subsample, resilience was more strongly associated with self-regulatory emotional intelligence, whereas in the follower subsample sense of coherence showed a more pronounced independent contribution. It should be emphasized that these are descriptive patterns observed in group-specific regression models and do not reflect statistically significant moderation effects; they should therefore be interpreted with caution and not generalized as structural differences between hierarchical roles.

## Conclusion

Based on the empirical findings, an integrated organizational–psychological model emerges in which resilience is not conceptualized as an isolated individual disposition, but rather as an operational capacity shaped through the interaction of personal and organizational resources.

Emotional intelligence was empirically differentiated in the sample into two distinct dimensions: adaptive-social and self-regulatory factors. The former and the latter factors functioned as important predictors of resilience, though the latter was revealed to be the most important predictor of the construct in the study, with the highest beta weight (.450, $p < .001$). This result suggests that the microfoundation of organizational stability can be found in the internal regulation of emotions, tolerance to stress, and control of impulses. Sense of coherence was found to have an independent and significant association with the construct of resilience, with beta weight equal to .171, $p = .002$, and was also revealed to have a partial mediation effect in the EI-resilience association. In the mediation model, the direct effect of EI on the construct of resilience was found to be diminished, though still statistically significant, from self-regulatory $\beta = .450$ to $\beta = .377$.

With respect to organizational role, the moderation analyses confirmed structural invariance across leader and follower groups: none of the interaction effects reached statistical significance. At a descriptive level, group-specific regression models suggested a pattern in which leader resilience showed stronger association with self-regulatory emotional intelligence ($\beta = .652$, $p < .001$), while follower resilience showed a more pronounced independent contribution of sense of coherence ($\beta = .262$, $p < .001$). These patterns should be interpreted cautiously as exploratory, non-significant trends rather than established structural differences, and their replication in larger, role-balanced samples would be necessary before drawing firm conclusions. To the extent that these descriptive patterns prove replicable, they would provide a preliminary basis for considering role-sensitive approaches to resilience development in safety-critical organizations.

## Discussion and theoretical implications

Most of the study's hypotheses received empirical support. Emotional intelligence was positively associated

with resilience (H1) and sense of coherence (H2), while mediation analyses confirmed a partial mediating role of sense of coherence (H3). Self-regulatory emotional intelligence emerged as the strongest predictor of resilience (H4). The moderating role of organizational position (H5) was not statistically supported; however, group-specific patterns suggest differences in the relative importance of psychological resources across hierarchical levels.

The theoretical contribution of the study can be summarized in three points. First, it refines the micro-mechanisms linking emotional intelligence and resilience. Second, it positions sense of coherence (SOC) as an interpretive stabilizer mediating between emotional resources and resilient functioning. Third, it conceptualizes resilience in safety-critical industrial environments as a psychological microfoundation of organizational reliability.

## Mechanistic refinement of the EI–resilience relationship

Although meta-analytic evidence consistently links emotional intelligence with workplace outcomes, the mechanisms underlying this relationship remain only partially understood (Joseph & Newman, 2010; Miao et al., 2017; O'Boyle et al., 2011). The present findings contribute to clarifying this relationship by identifying two empirically derived EI dimensions and demonstrating that the self-regulatory component is a substantially stronger predictor of both sense of coherence (β = .489) and resilience (β = .450) than the adaptive–social dimension.

This pattern supports a mechanistic interpretation of resilience grounded in emotion regulation and attentional control under stress (Bonanno & Burton, 2013; Double et al., 2022). Rather than reflecting general social competence, resilience appears to depend primarily on internal regulatory capacities–particularly impulse control, stress tolerance, and emotional stability (Armstrong et al., 2011; Schneider et al., 2013). These findings therefore clarify the functional pathway through which emotional intelligence contributes to adaptive functioning in demanding organizational environments.

The effect sizes observed in the present study warrant contextual evaluation. The standardized coefficient for self-regulatory emotional intelligence as a predictor of resilience (β = .450) is consistent with the correlation reported by Armstrong et al. (2011) between intrapersonal EI components and psychological resilience (r = .47), and exceeds the mean effect observed in broader meta-analyses of EI and job performance outcomes (r = .28; Miao et al., 2017). The overall explained variance in resilience ($R^2$ = .507) is notably high for a self-report study of this kind, which warrants some caution in interpretation. One plausible alternative explanation is that the strong associations partly reflect construct overlap rather than independent predictive pathways: the self-regulatory EI dimension – comprising stress tolerance, impulse control, and emotional stability – shares conceptual content with the CD-RISC-10 resilience items, which also assess the capacity to cope under stress and recover from adversity. This overlap does not invalidate the findings, but it suggests that the observed β-values may overestimate the degree to which EI and resilience represent functionally distinct constructs. Future research employing ability-based EI measures alongside trait-based resilience assessments would allow a more conservative test of this relationship. A further alternative explanation concerns the potential confounding role of broad personality dimensions, particularly emotional stability, which is known to correlate with EI, SOC, and resilience simultaneously (Petrides, 2010). The absence of a personality control variable represents a boundary condition of the present findings.

## Sense of coherence as an interpretive stabilizer

Sense of coherence has long been identified as a protective psychological resource (Eriksson & Lindström, 2006). The present study extends this perspective by conceptualizing SOC as a mediating interpretive mechanism linking emotional intelligence and resilience. Sense of coherence emerged as an independent predictor of resilience (β = .171) and partially mediated the relationship between emotional intelligence and resilience (self-regulatory pathway: β = .450 → .377).

This pattern is theoretically consistent with two major frameworks. Within the Job Demands–Resources (JD–R) model, personal resources influence outcomes partly through interpretive processes that structure the perception of job demands (Bakker & Demerouti, 2007; Vogt et al., 2016). Similarly, Conservation of Resources (COR) theory conceptualizes resilience as the capacity to mobilize resources and prevent resource loss under stress (Hobfoll, 1989). In this context, sense of coherence functions as a resource integrator that supports structured interpretation of complex work environments.

The three-stage mechanism outlined in the theoretical section finds support in the present empirical pattern. The substantially stronger predictive weight of the self-regulatory EI dimension – relative to the adaptive–social dimension – for both sense of coherence (β = .489 vs. β = .245) and resilience (β = .450 vs. β = .279) is consistent with the proposed affective filtering function: it is specifically the regulatory capacities of impulse control, stress tolerance, and emotional stability that reduce affective load and thereby enable coherent situational appraisal. The partial rather than full mediation of sense of coherence further suggests that emotional self-regulation also contributes to resilience through a parallel pathway – most plausibly through direct behavioral regulation under stress – while the interpretive stabilization function of SOC constitutes a distinct and independent mechanism. This dual-pathway architecture is theoretically coherent with the cascade model proposed by Joseph and Newman (2010), in which emotion regulation influences outcomes both directly and through downstream cognitive processes.

While this dual-pathway architecture is theoretically coherent, the independent contribution of sense of coherence to resilience was relatively modest (β = .171) compared to the direct effects of the EI dimensions, and warrants closer examination. This pattern of partial

rather than full mediation suggests that sense of coherence captures a real but limited portion of the pathway between emotional intelligence and resilience – consistent with Feldt et al.'s (2000) finding that SOC functions as a mediator in workplace stress models, though not as a dominant pathway. One interpretation is that the three SOC components – comprehensibility, manageability, and meaningfulness – operate at a higher level of cognitive abstraction than the moment-to-moment regulatory processes captured by EI, and therefore contribute to resilience through a slower, more dispositional channel. An alternative interpretation, however, is that the partial mediation partly reflects the measurement properties of the instruments: the SOC-13 and the CD-RISC-10 both contain items assessing perceived control and coping efficacy, which may produce residual overlap inflating their shared variance. This possibility cannot be ruled out in the present cross-sectional, single-source design, and represents a relevant limitation when interpreting the mediation effect.

### Resilience as a microfoundation of organizational reliability

Organizational resilience research increasingly conceptualizes resilience as a capability enabling anticipation, response, and learning (Duchek, 2020; Vogus & Sutcliffe, 2007; Williams et al., 2017). The present findings complement this perspective by highlighting the psychological processes underlying resilient functioning. In safety-critical environments, emotional self-regulation appears to function as a primary mechanism supporting stable decision-making and operational reliability (Clarke, 2010).

This study therefore reconnects system-level resilience perspectives with their psychological microfoundations. Organizational stability emerges not only from structural arrangements but also from individual processes of emotional regulation and coherent situation appraisal (Lengnick-Hall et al., 2011; Duchek, 2020).

### Consistency with and divergence from prior research

Taken together, the present findings are largely consistent with the existing literature on emotional intelligence, sense of coherence, and resilience, while offering a degree of specificity that extends prior work in meaningful ways. The primacy of self-regulatory over adaptive–social EI in predicting resilience replicates and extends the findings of Armstrong et al. (2011) and aligns with the cascade model of Joseph and Newman (2010), in which emotion regulation constitutes the most proximal link to performance outcomes. The present study adds to this picture by demonstrating that this primacy holds not only in general or clinical populations but also in an experienced industrial workforce population embedded in operationally demanding organizational environments. The partial mediating role of SOC extends Feldt et al.'s (2000) workplace mediation findings to a new nomological context, situating SOC within a broader personal resource chain rather than treating it as a standalone protective factor.

### Role invariance and differentiated resource weighting

Although moderation analyses indicated that the structural relationships among variables were invariant across leader and follower groups, descriptive analyses revealed differences in the relative weighting of resources. For leaders, resilience was primarily associated with self-regulatory emotional intelligence, whereas for followers sense of coherence played a more substantial role. It should be noted, however, that these are descriptive patterns not supported by significant moderation effects.

This pattern suggests that resilience mechanisms are structurally stable but contextually weighted. While the basic psychological architecture–emotional self-regulation combined with coherent interpretation–remains consistent, organizational roles may influence how these resources are mobilized. Such differentiated resource activation aligns with both JD–R and COR frameworks, which emphasize the role of contextual demands in shaping resource utilization (Bakker & Demerouti, 2007; Hobfoll, 1989).

## Practical Implications

The findings carry several concrete implications for resilience development in safety-critical organizations. The primacy of self-regulatory emotional intelligence – encompassing impulse control, stress tolerance, and emotional stability – as the strongest predictor of resilience suggests that effective intervention programs should prioritize these specific capacities over broader social or interpersonal competencies. In practical terms, this implies that training programs for employees in operationally demanding environments should include components targeting: (1) stress inoculation and controlled exposure to high-demand scenarios to build stress tolerance; (2) cognitive defusion and impulse regulation techniques drawn from acceptance-based behavioral approaches; and (3) reflective practice exercises that develop awareness of one's own emotional reactivity patterns under operational pressure. These components are distinct from generic communication or teamwork training and address the specific regulatory capacities that the present findings identify as most critical.

The independent contribution of sense of coherence to resilience further suggests that organizational design factors play a role alongside individual competencies. Specifically, the comprehensibility, manageability, and meaningfulness of the work environment can be actively supported through organizational measures such as clearly defined role responsibilities, transparent decision-making processes, structured communication about organizational goals, and meaningful feedback on individual contributions. These structural conditions do not replace individual psychological development but create the interpretive context within which self-regulatory capacities can be most effectively deployed.

## Limitations and Future Research Directions

Several limitations should be considered when interpreting the findings of this study. First, the research relies on cross-sectional data, which does not allow for definitive causal inference. Although the mediation model is theoretically grounded and statistical assumptions were met, examining the temporal dynamics among emotional intelligence, sense of coherence, and resilience would require longitudinal designs or confirmatory structural equation modeling (SEM).

Second, the data were collected using self-report questionnaires, which may introduce the risk of common method bias. While the differentiated pattern of relationships and the non-significant interaction effects reduce this concern, future research could strengthen the robustness of the model by incorporating objective indicators or multi-source data.

Third, although the participating organizations operate in sectors that are widely recognized as safety-critical – particularly railway transport, heavy industry, and automotive manufacturing – the study did not include a direct measure of individual-level occupational risk exposure. The sample encompasses a range of job roles varying in their proximity to safety-critical operations, from operational positions such as train drivers, maintenance technicians, and crane operators to administrative and support functions. Accordingly, the extent to which the theoretical framing of high-risk organizational environments applies uniformly across all participants should be interpreted with appropriate caution. Future research would benefit from incorporating explicit occupational risk criteria or role-level safety exposure indicators as contextual variables, which would allow more precise testing of the model's boundary conditions within safety-critical populations.

Regarding role differences, moderation analyses did not provide statistical support for structural differences between leaders and followers. However, the observed variation in the relative weighting of psychological resources suggests that further research using larger samples and measurement invariance testing could provide a more precise understanding of role-related dynamics.

Future research could extend the present findings by applying longitudinal or multilevel designs, testing the model using structural equation modeling, and linking resilience to objective organizational outcomes such as safety incidents, error rates, or performance indicators.

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BENCE PISTRUI – PETRA JENEI

# ORGANIZATIONAL STRATEGIES FOR ETHICAL AND SUSTAINABLE AI IMPLEMENTATION

# SZERVEZETI STRATÉGIÁK AZ ETIKUS ÉS FENNTARTHATÓ MI-BEVEZETÉSHEZ

The rapid diffusion of artificial intelligence (AI) has intensified debate about its dual role as a driver of efficiency and a source of environmental, social, and ethical challenges. These challenges include the growing energy and water demands of data centers, hardware-related emissions and e-waste, data governance risks, workforce concerns, and increasing regulatory pressure. While prior research highlights AI's sustainability potential, less is known about how organizations translate ethical and sustainability principles into concrete implementation strategies. This study examines responsible AI adoption under sustainability constraints, using the Technology-Organization-Environment framework extended with ESG and ethics considerations, and the Triple Bottom Line perspective to interpret outcomes. Empirical insights are based on five semi-structured expert interviews with senior executives, AI specialists, and sustainability professionals across industries and national contexts. The findings show that AI supports efficiency, predictive analytics, and sustainability monitoring, but responsible deployment depends on readiness, data quality, workforce capabilities, and governance structures.

Keywords: **AI governance, Triple Bottom Line (TBL), Technology-Organization-Environment (TOE) framework, digital transformation**

A mesterséges intelligencia (MI) gyors terjedése felerősítette azokat a vitákat, amelyek az MI kettős szerepét vizsgálják: egyrészt a hatékonyság növelésének hajtóerejeként, másrészt környezeti, társadalmi és etikai kihívások forrásaként. Ezek a kihívások magukban foglalják az adatközpontok növekvő energia- és vízigényét, a hardverekhez kapcsolódó kibocsátásokat és az elektronikai hulladékot, az adatirányítási kockázatokat, a munkaerővel kapcsolatos aggályokat, valamint az egyre fokozódó szabályozói nyomást. Bár a korábbi kutatások kiemelik az MI fenntarthatósági potenciálját, kevesebb az ismeret arról, hogy a szervezetek miként ültetik át az etikai és fenntarthatósági elveket konkrét megvalósítási stratégiákká. A tanulmány a felelős MI-alkalmazást vizsgálja fenntarthatósági korlátok mellett, a technológia-szervezet-környezet (Technology-Organization-Environment, TOE) keretrendszer ESG- és etikai szempontokkal kibővített változatának alkalmazásával, míg az eredmények értelmezéséhez a Triple Bottom Line (TBL) megközelítést használja. Az empirikus eredmények öt, félig strukturált szakértői interjún alapulnak, amelyekben felsővezetők, MI-szakértők és fenntarthatósági szakemberek vettek részt különböző iparágakból és nemzeti kontextusokból. Az eredmények azt mutatják, hogy az MI támogatja a működési hatékonyságot, a prediktív analitikát és a fenntarthatósági teljesítmény nyomon követését, ugyanakkor a felelős alkalmazás nagymértékben függ a szervezeti felkészültségtől, az adatok minőségétől, a munkaerő kompetenciáitól és a megfelelő irányítási struktúráktól.

Kulcsszavak: **mesterségesintelligencia-irányítás, hármas értékteremtés elmélete, technológia-szervezet-környezet keretrendszer, digitális transzformáció**

**Funding/Finanszírozás:**
The authors did not receive any grant or institutional support in relation with the preparation of the study.
A szerzők a tanulmány elkészítésével összefüggésben nem részesültek pályázati vagy intézményi támogatásban.

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The article was received: 01. 02. 2026, revised: 06. 05. 2026 and 19. 06. 2026, accepted: 23. 06. 2026.
A cikk beérkezett: 2026. 01. 02-án, javítva: 2026. 05. 06-án és 2026. 06. 19-én, elfogadva: 2026. 06. 23-án.
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Examining the dual impact of artificial intelligence on operational efficiency and sustainability has become increasingly important, as the rapid expansion of AI adoption contrasts with its growing resource demands. In operational terms, AI enhances profitability by processing large datasets, automating complex decisions, and improving forecasting accuracy, enabling organizations to operate more efficiently and responsively. At the same time, AI is widely regarded as an enabler of sustainable performance, particularly through data-driven environmental decision-making, energy optimization, environmental risk prediction, and improved resource efficiency (Jorzik et al., 2024; Alzoubi & Mishra, 2024). As a result, AI is often positioned as a technological contributor to the United Nations Sustainable Development Goals and the development of more resilient economic and food systems.

In this study, sustainability is treated as the overarching objective of long-term value creation, interpreted through the Triple Bottom Line dimensions of economic performance, environmental protection, and social well-being. Environmental responsibility refers specifically to AI-related energy use, water consumption, emissions, hardware intensity, and electronic waste. ESG is used as an organizational lens that translates sustainability expectations into governance, reporting, accountability, and stakeholder management practices. Ethics refers to the responsible design and use of AI systems, including transparency, fairness, privacy, accountability, human oversight, and the social consequences of automation. Accordingly, the article examines responsible AI implementation as the process through which firms align technological adoption with ESG expectations, ethical principles, and TBL sustainability outcomes.

This strategic interpretation of digital technologies is also reflected in the management literature. Digitalization and data-driven systems should not be understood merely as operational efficiency tools, but as strategic resources that reshape organizational capabilities, decision-making, and long-term value creation (Varga & Csesznák, 2019). Prior studies further show that digital transformation outcomes depend on whether technologies are strategically embedded and aligned with broader organizational objectives rather than adopted in an ad hoc or technology-driven manner (Bauer & Agárdi, 2020). From this perspective, AI influences not only competitiveness, but also how firms balance economic performance with environmental and social responsibilities.

Despite its sustainability-enabling potential, AI adoption creates a central dilemma. While AI can support environmental optimization and responsible resource management, the technology itself is increasingly resource intensive. Advanced AI systems require substantial computational capacity for both training and inference, while data center infrastructure places pressure on energy and water resources. The production, deployment, and disposal of AI-related hardware, including servers, GPUs, and specialized chips, also generate environmental costs through resource extraction, manufacturing emissions, and electronic waste (Varriale et al., 2026; Litvinets, 2024; Hordieiev et al., 2025). Model selection therefore plays an important role in determining AI's environmental impact, as complex architectures generally consume more energy than simpler analytical or classification models.

These dynamics position AI as both a potential solution to sustainability challenges and a source of new environmental risks. As AI systems scale across industries, their cumulative energy, water, and hardware-related impacts raise concerns about the long-term sustainability of widespread AI deployment. This tension highlights the importance of examining not only what AI can achieve, but also how it is implemented and governed within organizations.

These dynamics position AI as both a potential solution to sustainability challenges and a source of new environmental risks. In line with the discourse on responsible digital transformation, this duality underscores the need for a strategic and governance-oriented examination of AI adoption that extends beyond short-term efficiency gains (Szabó & Csontos, 2021). Accordingly, the present study focuses on how organizations at the strategic and operational levels can implement AI in ways that ethically balance economic performance with environmental and social considerations, addressing the trade-offs inherent in the Triple Bottom Line.

Despite the growing body of research on AI and sustainability, relatively little is known about how organizations translate ethical and sustainability-oriented principles into concrete AI implementation strategies in practice, an issue this paper aims to examine. In light of these complexities, he aim of this study is to examine how organizations translate ethical and sustainability-oriented principles into concrete AI implementation strategies, and how they balance AI's operational benefits with its environmental, social, and governance-related risks.

Based on this aim, the study addresses the following research questions:

*RQ1: How do experts perceive AI's contribution to operational efficiency, competitiveness, and sustainability-related monitoring?*
*RQ2: What internal enablers and barriers shape the ethical and environmentally responsible implementation of AI within organizations?*
*RQ3: How do market expectations and regulatory pressures influence organizational strategies for balancing AI-driven efficiency with environmental and social responsibility?*

## Literature review

This literature review distinguishes between AI's sustainability potential, its sustainability-related risks, and the governance mechanisms needed for responsible implementation. Sustainability is understood through the Triple Bottom Line, covering economic, environmental, and social outcomes, while environmental responsibility refers specifically to AI's ecological effects, such as energy use, emissions, water consumption, hardware demand, and electronic waste. ESG is treated as a managerial and

reporting lens, while AI ethics focuses on transparency, fairness, privacy, accountability, human oversight, and workforce implications. Based on this logic, the review discusses AI as both an enabler and a challenge for sustainability, before introducing the organizational and theoretical frameworks used in the study.

## Impacts of AI

Understanding both the enabling and challenging aspects of AI adoption is essential for examining responsible implementation. AI can improve efficiency, decision-making, innovation, and sustainability monitoring, but it also introduces technological, organizational, environmental, and ethical risks. Therefore, this section reviews AI's dual role as both an enabler of sustainability and a source of sustainability-related challenges.

### *AI as an enabler of sustainability*

Artificial Intelligence serves as a critical enabler of sustainability by strengthening data-driven decision-making, optimizing resource use, and supporting environmentally conscious innovation across sectors. Through its capacity to analyze large volumes of information, anticipate risks, and automate complex processes, AI enhances organizational capabilities to reduce environmental impacts and develop greener production systems (Kupi, 2025). When combined with complementary digital technologies such as the Internet of Things (IoT) and Distributed Ledger Technology (DLT), AI contributes to more efficient monitoring, improved transparency, and the creation of new sustainability-oriented business models (Porkodi et al., 2025).

Evidence from an emerging-economy the agricultural sector illustrates how AI significantly improves information processing, supports production problem-solving, and enables environmentally responsible product innovation. It accounts for more than 80% of the ability to integrate diverse data sources, support complex decision-making, and enhance recycling-related processes, while also driving green product innovation through low-resource raw material selection and recyclable product design (Monsalve-Castro et al., 2025).

Studies in manufacturing, logistics, and supply-chain contexts suggest similar enabling effects. AI-driven strategies outperform traditional digital approaches by not only optimizing energy use and reducing waste but also fostering new solutions for carbon removal and environmental restoration (Rashid et al., 2024). Firms that adopt AI demonstrate greater improvements in environmental performance compared to those relying solely on IoT-based enhancements, emphasizing AI's proactive and predictive contribution to sustainability management (Monroy-Osorio, 2024).

Within local energy community and smart-grid contexts, the integration of AI with IoT (AIoT) further reinforces sustainability goals. In emerging local energy communities, IoT-enabled smart grids facilitate real-time monitoring of energy consumption and generation, allowing prosumers and system operators to manage resources more efficiently (Podrecca et al., 2024). AI enhances this infrastructure by optimizing DLT applications, improving their efficiency, security, and energy performance, and enabling more reliable and transparent citizen-centered energy models. The combination of AI, IoT, and DLT thus supports decentralised energy prosumption and contributes to more resilient, low-carbon energy ecosystems (Bokolo, 2024).

### *AI as a source of sustainability challenges*

Although AI has strong potential to advance sustainability, its implementation within green and sustainable supply chains is constrained by several significant barriers. Many challenges arise from the technological, organizational, and regulatory complexities involved in implementing AI into current operations, especially in resource-limited sectors and developing countries. These limitations reduce the ability of AI to fully support circularity, reduce waste, or optimize environmental outcomes (Baumgartner et al., 2025).

A major concern relates to the environmental cost of AI itself. High computational demands, intensive data processing, and the use of non-renewable energy sources can increase energy consumption and carbon emissions, limiting the net sustainability benefits of AI systems (Luo & Zhang, 2025). Furthermore, the successful integration of AI technologies is strongly dependent on the availability of technical skills, which remains limited, particularly among SMEs (Khan et al., 2024). High initial investment costs, specialized skill requirements, and insufficient training all hinder adoption and expand the capability gap between advanced and emerging economies (Luo & Zhang, 2025).

Data-related issues also constrain AI's effectiveness. High-quality, comprehensive datasets are essential for predictive and optimization models, yet supply chains often lack reliable customer behavior data, historical trends, or standardized information. Variability in data reduces model accuracy and requires firms to deploy more efficient algorithms to compensate (Bokolo, 2024). These challenges are further compounded by the limited adoption of circular economy principles and the scarcity of AI applications focused on end-of-life product management, despite the technology's potential to improve resource recovery and waste reduction (Fu et al., 2024).

Technical and integration-related barriers remain substantial. Organizations in technologically complex and regulated contexts may struggle to align AI solutions with sustainability objectives, manage data quality, meet regulatory requirements, and ensure compatibility with Industry 4.0 systems (Bokolo, 2024). Concerns about data privacy, cybersecurity, and compliance with evolving legal frameworks further slow implementation. Resistance to change also persists, as stakeholders may hesitate to adopt AI due to perceived risks, unclear benefits, or high implementation costs (El Saadani Gazar et al., 2024).

These obstacles are amplified in certain industries, where sector-specific requirements complicate AI deployment. Fields such as healthcare, agriculture, and financial

supply chains face unique challenges related to interoperability, validation standards, regulatory restrictions, infrastructure limitations, and environmental variability. In many cases, limited financial and technical resources restrict organizations' ability to integrate sophisticated technologies effectively (Khan et al., 2024).

Finally, the complexity of green supply chain management poses an additional barrier. Implementing green practices requires substantial process adjustments, and manufacturers often struggle to enhance product sustainability using existing tools. This highlights the need for more targeted research, customized AI solutions, and increased funding to support small and medium enterprises in overcoming governance and data management challenges (Porkodi et al., 2025).

## Company perspectives

This section reviews research and practical insights on the ethical and strategic use of AI, focusing on how organizations balance technological innovation with social, environmental, and economic responsibilities. It provides background for understanding how ethical principles are translated into responsible AI implementation.

### *Ethical, organizational, and sustainability perspectives on AI adoption*

Recent study emphasizes that ethical AI governance is deeply related to comprehensive corporate responsibility frameworks, organizational strategy, and the human implications of automation. The increasing integration of AI and automation requires that organizations implement governance frameworks that combine technical efficiency with stakeholder well-being, environmental sustainability, and ethical practices (Rastogi & Pandita, 2025). Corporate Social Responsibility (CSR) plays a role in this shift, as firms are expected to operate transparently and be accountable to employees, customers, and the communities. Effective CSR strengthens reputation, stakeholder trust, and long-term sustainable performance, reinforcing the need for AI governance mechanisms that reflect ethical practices and social expectations (Gandía et al., 2024).

Environmental sustainability adds another important dimension to ethical governance. With the growing urgency of climate challenges, businesses are transitioning from linear to circular models that prioritise resource efficiency, waste reduction, and system-wide coordination across value chains (Varriale et al., 2026). Circular economy principles require firms not only to minimise negative ecological impacts but also to collaborate with stakeholders to redesign products, materials, and processes. AI governance must therefore ensure that automation and data-driven systems support these goals, enabling responsible resource use, promoting transparency, and preventing technologies from reinforcing unsustainable practices (Gandía et al., 2024).

Automation and AI adoption introduce further governance demands related to technological oversight and organisational alignment. Automation has evolved into a strategic driver of efficiency, quality, and competitive differentiation, supported by advances in machine learning, natural language processing, and robotic process automation (Rashid et al., 2024). While these tools streamline operations and reduce costs, they also heighten the need for governance frameworks that manage risks such as job displacement, dependence on digital tools, and the ethical implications of delegating decisions to intelligent systems. Ensuring responsible automation requires policies that address integration challenges, safeguard data quality, and maintain regulatory compliance, while also preparing organisations to respond to emerging technological capabilities (Gandía et al., 2024).

A human-centered perspective is equally essential in ethical AI governance. Employees' skills, motivation, and professional development directly affect how technologies are adopted and embedded within organisational culture. Governance structures must therefore support continuous learning, skills-matching, and equitable adaptation to changing roles (Di Chiacchio et al., 2026). This includes ensuring that automation enhances rather than diminishes career opportunities, reduces workload-induced stress, and promotes employee engagement instead of eroding it. Aligning managerial and employee perspectives on the value and risks of automation is crucial to supporting workforce resilience, mitigating fears of job loss, and maintaining trust in technology-enabled workplaces (Gandía et al., 2024).

Overall, current research underscores that ethical AI governance is not limited to technical regulation but must integrate CSR principles, environmental objectives, responsible automation practices, and workforce-centred policies. This holistic approach enables organisations to leverage AI strategically while preserving sustainability, accountability, and stakeholder wellbeing (Gandía et al., 2024).

### *Strategic AI implementation*

Strategic AI implementation plays a decisive role in enabling organizations to enhance economic, environmental, and technological sustainability. Across contemporary research, AI is portrayed not merely as an operational tool but as a transformative strategic asset that strengthens resilience, fosters innovation, and supports long-term sustainable development.

From an economic and organizational standpoint, AI improves adaptability, fiscal stability, and value creation. Pietrzak (2025) shows that AI-enabled predictive analytics increase the accuracy of budgeting, forecasting, and cash flow management by providing firms with data-driven insight and decision agility. Customer-oriented applications, such as recommendation platforms and conversational agents, further improve service quality and personalization, supporting revenue stability and customer retention (Jorzik et al., 2024). AI also supports procurement, supplier evaluation, pricing, innovation processes, and ESG data collection, thereby contributing to cost reduction, transparency, and regulatory compliance (Pietrzak, 2025).

Beyond large organizations, strategic AI implementation is also relevant for micro, small, and medium enterprises (MSMEs). Chotisarna and Phuthong (2025) identify a "green cluster" of AI-related technical advancements, including big data analytics, machine learning, deep learning, and digital transformation, which can improve competitiveness and innovation. Evidence from over 16,000 MSMEs shows that AI adoption depends on interactions between internal capabilities and external support, demonstrating that digital transformation requires both organizational readiness and ecosystem collaboration. Big data analytics can also support supply chain coordination and risk management, especially during disruptions (Podrecca et al., 2024). Nonetheless, cost and technical complexity remain significant barriers, highlighting the need for strategic support structures and phased AI integration (Chotisarna & Phuthong, 2025).

At the environmental level, strategic AI implementation is strongly linked to green innovation and improved environmental performance. Xu et al. (2025) suggest that AI-driven technical innovation can enhance corporate environmental sustainability when combined with supportive legislation and responsible governance. At the firm level, integrating AI into environmental initiatives, particularly through IoT-enabled monitoring of energy use, emissions, and waste, helps organizations identify inefficiencies, minimize resource consumption, and reduce environmental impact (Alzoubi & Mishra, 2024). AI-enabled knowledge management further strengthens environmental problem-solving by processing large volumes of sustainability data and supporting data-driven decision-making (Rastogi & Pandita, 2025). Firms with strong absorptive capacity are better able to internalize and apply new environmental knowledge, showing that strategic AI implementation must be coupled with cultural commitment and organizational learning (Xu et al., 2025).

Complementing these insights, Zhang (2025) demonstrates that AI adoption positively influences enterprise-level green innovation by improving resource allocation, optimizing decisions, and enabling more sustainable technological development. This effect appears to persist over time, while mature firms may benefit more due to their accumulated experience, infrastructure, and network ties (Kupi, 2025).

Taken together, current research shows that strategic AI implementation is multidimensional, extending across economic functions, innovation processes, organizational capabilities, and environmental performance. Successful integration requires not only technological tools but also supportive governance structures, absorptive capacity, and alignment with sustainability-oriented objectives. However, while prior studies document both the opportunities and risks of AI, less attention has been paid to how organizations translate ethical and sustainability-oriented principles into concrete implementation strategies. Addressing this gap is essential for understanding how AI can be governed and deployed to support long-term environmental and social sustainability alongside economic performance.

## Theoretical frameworks

This study applies the Technology-Organization-Environment (TOE) framework and the Triple Bottom Line (TBL) perspective. TOE is used to examine the technological, organizational, and external environmental factors that shape AI adoption, while TBL is used to interpret the economic, environmental, and social outcomes of AI implementation. ESG and AI ethics are treated as governance lenses that clarify how organizations manage responsibility, accountability, transparency, and sustainability during AI adoption.

### *Technology-organization-environment*

From a theoretical standpoint, this study extends the traditional Technology-Organization-Environment (TOE) framework by incorporating ESG + Ethics (Environmental, Social, Governance + Ethical) considerations to better explain artificial intelligence (AI) adoption. The TOE framework has been widely used to analyze organizational technology adoption by focusing on technological characteristics, organizational readiness, and environmental pressures (Tornatzky & Fleischer, 1990). However, prior research has noted that TOE primarily emphasizes operational feasibility and efficiency, offering limited insight into the ethical, social, and sustainability implications of advanced digital technologies. (Baker, 2012; Oliveira & Martins, 2011; Senna et al., 2023).

This limitation is particularly evident in the case of AI, which introduces governance challenges related to data privacy, transparency, accountability, and algorithmic bias. Ethical AI research highlights that AI systems function as socio-technical technologies whose impacts extend beyond organizational boundaries and directly affect societal outcomes (Floridi et al., 2018; Jobin et al., 2019). As a result, scholars increasingly argue that traditional technology adoption frameworks require conceptual extension to capture responsible and sustainable AI implementation.

In parallel, research on responsible innovation and corporate sustainability emphasizes the growing importance of environmental, social, and governance considerations in strategic decision-making. Responsible innovation frameworks stress the need to align technological development with ethical acceptability and long-term societal value (Stilgoe et al., 2013; von Schomberg, 2013), while ESG-oriented research demonstrates that sustainability and governance practices significantly influence organizational legitimacy and performance (Eccles et al., 2014; Gillan et al., 2021).

Building on these insights, this study integrates ESG + ETHICS dimensions into the TOE framework to provide a more comprehensive lens for analyzing AI adoption. TOE dimensions capture core adoption capabilities, whereas ESG + ETHICS dimensions explicitly address sustainability objectives, ethical risks, and governance mechanisms shaping AI deployment. This integrated approach is particularly relevant for SMEs and organizations operating in emerging economies, where institutional support and regulatory clarity are often limited, increasing the risks associated with ungoverned AI adoption (Dwivedi et al.,

2021; Kittipanyangam et al., 2025). By linking AI adoption with responsible innovation, the extended TOE + ESG + ETHICS framework enables a holistic assessment of both adoption drivers and sustainability outcomes.

*Triple Bottom Line*

Systems theory provides a foundational perspective for analyzing the Triple Bottom Line (TBL) framework, which integrates economic, environmental, and social dimensions of sustainability. By emphasizing the interconnections among system components, this approach enables a holistic understanding of how these dimensions interact. In particular, systems theory highlights the relationships among subsystems, allowing sustainability outcomes to be examined through feedback loops, trade-offs, and synergies (Kusmendar & Normasari, 2025). Such a systems-oriented lens facilitates informed decision-making in complex sustainability contexts, where interventions in one dimension such as environmental initiatives can produce significant effects on economic and social outcomes.

The TBL framework operationalizes systems thinking by promoting a balanced approach to economic viability, social equity, and environmental protection (Kusmendar & Normasari, 2025). It has been increasingly implemented in corporate sustainability practices as a strategic tool to strengthen organizational resilience, stakeholder accountability, and long-term value creation. From a systems perspective, effective TBL adoption requires continuous learning and adaptive governance to respond to evolving sustainability challenges. Systems-based methods including system dynamics, agent-based modeling, and input-output analysis, have been applied to evaluate the impact of policy interventions on sustainable development, reinforcing TBL's focus on interdependence, feedback processes, and non-linear change dynamics (Kusmendar & Normasari, 2025).

This theoretical foundation underpins the present study's objective to examine how systemic, cross-disciplinary, and digital integration strategies influence TBL implementation across sectors. Moreover, the incorporation of digital technologies into sustainability reporting frameworks, such as the Global Reporting Initiative (GRI), underscores the growing synergy between Industry 4.0 enablers and TBL dimensions, particularly in manufacturing and service industries.

Taken together, the TOE framework extended with ESG + ETHICS dimensions provides a structured lens for analyzing the drivers, enablers, and constraints of AI adoption, while the Triple Bottom Line framework offers an outcome-oriented perspective on the economic, environmental, and social implications of these adoption processes. In this study, TOE + ESG + ETHICS is used to examine how organizations approach AI implementation at strategic and operational levels, whereas TBL is applied to interpret the sustainability trade-offs and performance outcomes associated with these practices. The combined use of these frameworks enables a holistic assessment of both the implementation logic and the sustainability consequences of AI adoption.

## Methodology

The methodology section describes the research design and data collection process applied in this study. It explains how the data were gathered, the criteria used for selecting the interviewees, and the reasoning behind their inclusion. Additionally, it outlines how the interview questions were developed and structured to address the research objectives. As our main methodology, we employed Directed Qualitative Content Analysis. Unlike purely inductive approaches where themes emerge from the data alone, our analysis was primarily driven by the integration of the TOE framework and ESG+E dimensions. This theoretical grounding ensures that the analysis remains aligned with established organizational and sustainability constructs while allowing for nuanced insights from expert participants. Consequently, deductive coding was based on the pre-defined elements of the TOE framework and ESG+E dimensions (Kibiswa, 2019).

### Data collection type

This study is rooted in the interpretivist paradigm, which seeks to understand organizational realities through the subjective experiences of experts (Alharahsheh & Pius, 2020). Therefore a semi-structured interview is a highly effective research method because it balances consistency with flexibility, making it particularly valuable for exploring complex or emerging topics such as AI and sustainability. This approach ensures that all participants address comparable core issues, improving reliability, while still capturing rich, nuanced insights that reflect their unique experiences, expertise, and perspectives (Kvale & Brinkmann, 2015). It is especially suitable when the aim is to understand not only what people think but why they think it, enabling the researcher to uncover underlying motivations, contextual factors, and previously unanticipated challenges or opportunities.

In management and organizational research, semi-structured interviews are widely applied in exploratory studies where the objective is to examine strategic decision-making, technology adoption, and organizational practices in contexts characterized by uncertainty and complexity (Saunders et al., 2019). As a result, this method supports a more holistic and grounded understanding of organizational realities, making it particularly appropriate for qualitative studies examining AI adoption, internal capabilities, and sustainability-related decision-making processes.

### Data collection process

The data gathering method for this research commenced with a focused LinkedIn search to discover AI specialists possessing relevant experience and knowledge in this field. Participants were identified through a focused LinkedIn search and selected through purposive sampling. LinkedIn was used as an access point rather than as the sole basis for determining expertise. Suitability was assessed based on publicly available professional information, including senior or expert-level roles (Chief Sustainability Officer, Chief Data Officer, and AI Executive Leaders*)*, direct experience with AI, data, sustainability, ESG, or governance, and

evidence of involvement in organizational or sector-level AI implementation. The sample was also designed to include geographic and sectoral diversity (e.g., UAE, UK, Spain, Finland, the EU AI Act versus the UAE AI Chapter*)*, allowing the study to capture perspectives from different regulatory and market contexts. Upon collecting an initial list of potential specialists, we started communication via LinkedIn messages explaining the research's objective and offering an invitation for their participation. Upon receiving positive responses, we arranged virtual meetings with Microsoft Teams, providing an accessible setting for synchronous discussions. In these meetings, we engaged in thorough discussions, obtaining significant insights regarding the experts' experiences with AI implementation and its effects on sustainability. Following to the sessions, we transcribed the discussions in order to document essential points and details, which subsequently formed the basis for analysis in the later stages of the research. This procedure facilitated a systematic and effective method for collecting expert insights, enabling a thorough comprehension of AI's function in sustainability practices.

## Interview profile

The interviewees for this research included a diverse group of experts, each bringing a unique perspective on AI, sustainability, and ESG (Environmental, Social, and Governance) practices. Participants were selected to ensure representation from different regions, markets, and professional environments in order to capture a broad range of insights on the topic. Additionally, all interviewees were chosen based on their demonstrated expertise, either through relevant academic research or substantial professional experience related to AI implementation, governance, or sustainability. This selection approach helped ensure that the findings reflect informed perspectives from experts with direct knowledge of the field. (Table 1).

## Interview questions

To structure the development of the interview questions, this study combined the Technology-Organization-Environment (TOE) framework with the Triple Bottom Line (TBL) sustainability model. The TOE framework was used to capture the technological, organizational, and external environmental factors influencing AI adoption, while the TBL framework provided the sustainability perspective by considering social, economic, and environmental impacts. As illustrated in Figure 1, the TOE dimensions were positioned along the vertical axis and the TBL dimensions along the horizontal axis, creating a matrix that guided both the design of the interview questions and the subsequent analysis. This structure allowed the study to systematically explore how different drivers of AI adoption interact with sustainability outcomes.

Figure 1

**Combined Framework**

| | TOE modell/ Sustainability | Social | Economic | Environment |
|---|---|---|---|---|
| Technological | AI relative advantage | | | |
| | AI readiness | | | |
| Organisational | Employee readiness | | | |
| | Support activities within organisation (eg. financing) | | | |
| | Main activities within organisation (eg. customer experience, manufacturing) | | | |
| Business External Environment | Market opportunities | | | |
| | Competitive pressure | | | |
| | Customer needs | | | |
| | Government involvement (support/barrier) | | | |

*Source: own editing*

Table 1

**Interview Profiles**

| Interview | Country | Position | Description |
|---|---|---|---|
| I.1 | UAE | Chief Sustainability Officer | His insights are grounded in extensive corporate sustainability experience, leadership roles, and expertise in integrating ESG strategies into organizational frameworks. |
| I.2 | Finland | Researcher | He specializes in advanced technologies relevant to corporate strategy. His academic background provides a strong theoretical foundation, and his research focuses on emerging technologies, including the strategic application of artificial intelligence in business sustainability. |
| I.3 | UK | Chief Data Officer | With deep expertise in data management and artificial intelligence, he works on leveraging data-driven insights to optimize business performance and sustainability initiatives, positioning him at the intersection of technology, data, and sustainability. |
| I.4 | Spain | AI expert, executive leader, and chair of the board of directors | Drawing on substantial experience in the healthcare sector, his expertise centers on applying AI technologies to improve operational efficiency and support sustainable practices, particularly in healthcare-related industries. |
| I.5 | UK | AI expert specializing in sustainability | His work focuses on the use of artificial intelligence to advance sustainability objectives, examining how AI-based solutions can reduce environmental impacts and foster sustainable business innovation. |

*Source: own editing*

Based on this framework, the interview questions (see Appendix 1) were grouped into three main areas corresponding to the TOE dimensions. First, technological aspects focused on the perceived relative advantage of AI and the technological readiness of organizations, including considerations related to efficiency, employee impact, and environmental implications such as energy consumption. Second, organizational factors addressed internal readiness for AI adoption, including employee preparedness, financial and operational support functions, and the integration of AI into core organizational activities. Third, external environmental factors examined the influence of market opportunities, competitive pressure, customer expectations, and government involvement on the responsible and sustainable implementation of AI. By structuring the interviews along these dimensions, the study ensured that each sustainability aspect of the TBL model could be examined in relation to the key drivers of AI adoption identified in the TOE framework.

## Results

We have organized the Results section based on the logic of the TOE model as it applies to AI, detailing each part through the lens of ESG+E considerations.

### Technological - perceived advantages and readiness

This subsection addresses RQ1 by analyzing experts' perceptions of AI's contribution to operational efficiency, competitiveness, and sustainability-related monitoring.

The interviews with AI experts revealed a multifaceted understanding of AI's perceived advantages and organizational readiness, highlighting both its promise and current limitations in sustainability and business contexts. Across the discussions, AI's role in operational efficiency, predictive analytics, environmental monitoring, employee support, and compliance emerged as recurring themes, although its impact varied depending on sector, organizational maturity, and regulatory context.

Several experts emphasized AI's capacity to improve operational performance and environmental efficiency. I.1 noted that predictive analytics are particularly valuable in energy-intensive industries, such as oil and gas, where demand forecasting and resource allocation are critical. AI can improve productivity, reduce costs, optimize resource use, minimize downtime, and support real-time monitoring of critical systems. This allows organizations to detect anomalies and intervene proactively, which is especially relevant for environmental management and compliance. I.1 also highlighted AI's role in climate action, including emission tracking and renewable energy optimization, contributing to a more sustainable energy mix.

I.3 similarly acknowledged AI's potential to improve environmental efficiency through initiatives such as smart energy monitoring systems, but noted that implementation often lags behind ambition, with projects only partially deployed and operationalization still limited. I.4 added that, in the commercial sector, AI applications are usually focused more on personalization and efficiency than direct environmental impact, although such technologies may still support more sustainable consumer decision-making.

Experts also consistently recognized AI's potential to enhance business performance. I.4 explained that adoption differs across sectors: startups and AI-native companies tend to show higher maturity, while traditional organizations are still integrating AI to improve customer experience and product performance. Examples include AI-driven customer support in financial services and personalized health-tech messaging to influence behavior change. I.5 added that AI can simplify complex sustainability compliance tasks by making regulatory knowledge more accessible, although regulatory acceptance remains a constraint. I.2 similarly highlighted AI's ability to automate tasks and generate insights, such as sentiment analysis from meeting transcripts, thereby improving oversight and decision-making.

AI's impact on employee well-being emerged as both a benefit and a challenge. I.1 and I.3 emphasized AI's potential to de-skill routine tasks and allow employees to focus on higher-value work. However, I.3 noted that tangible benefits for employee well-being remain limited, as many initiatives are still early-stage and their return on investment is difficult to measure. I.4 highlighted employee anxiety around job displacement, especially among lower-skilled workers, while I.2 stressed the importance of localized AI models to ensure accurate and culturally appropriate insights that support employees rather than produce skewed outcomes.

Organizational readiness varied considerably. I.5 described high preparedness through the integration of AI tools across operations, investment in training and expertise, and the appointment of senior AI leadership. In contrast, I.2 and I.3 noted that many organizations remain at an early stage, struggling to align AI with existing systems and strategies. Common barriers include immature technologies, limited financial and technical resources, difficulties in measuring ROI, and regulatory compliance requirements. As I.2 and I.5 emphasized, audit requirements such as the ESOS framework cannot always be met through AI-generated data, limiting AI's use in legally binding sustainability reporting.

In summary, AI is perceived as a transformative force for both operational and environmental efficiency, mainly through predictive analytics, automation, real-time monitoring, and data consolidation. However, its benefits depend strongly on organizational readiness, sector-specific maturity, data quality, regulatory acceptance, and strategic alignment. The findings also reveal a psychological duality for employees: AI can improve productivity and reduce routine work, but it may also increase job insecurity and anxiety. Overall, AI's advantages are significant, but they remain highly context-dependent and require careful governance, training, and change management.

### Organisational - the internal enablers and barriers

This subsection addresses RQ2 by examining the internal financial, technical, organizational, and workforce-related enablers and barriers that influence ethical and environmentally responsible AI implementation.

The interviews revealed a complex interplay of internal enablers and barriers affecting AI adoption. Financial, technical, and human-resource capabilities emerged as key enablers, while cost, data quality, organizational culture, and workforce readiness were repeatedly identified as major obstacles.

Financial readiness was both an enabler and a constraint. I.1 reported that AI had already been integrated across 60-70% of critical operational areas, showing strong commitment to adoption, but also emphasized that implementation costs remain substantial and can be especially prohibitive in developing regions. I.4 noted that while some companies can finance AI experimentation, few have the resources to develop proprietary models and therefore rely on pre-built or open-source solutions. Similarly, I.5 highlighted that smaller organizations often struggle to invest in AI infrastructure and expert personnel, although internal resources can help reduce development costs. I.2 added that many organizations still lack the investment capacity required for infrastructure and tailored AI models.

Technical readiness also functioned as both an enabler and a barrier. I.1 pointed to data synchronization challenges, particularly when integrating AI with legacy systems such as Enterprise Resource Management platforms, which can create inefficiencies and delays. I.5 stressed the importance of high-quality, well-structured data, as incomplete or inconsistent datasets compromise AI outputs and increase the risk of hallucinations or misleading results. I.2 further emphasized the need for culturally and contextually tailored AI models, since generic systems may produce inaccurate insights in specific organizational or regional contexts.

Employee readiness was another key determinant of successful adoption. I.1 described hands-on training programs and a largely IT-literate workforce, but also noted resistance among shop-floor employees concerned about job displacement. I.4 observed that employees are increasingly learning to use tools such as large language models, although adoption often remains ad hoc and lacks coordinated strategies or ethical frameworks. I.2 emphasized the need for reskilling, upskilling, and AI literacy across organizational levels as traditional roles evolve. I.3 reported similar challenges in academic settings, where professional staff showed more resistance than technically skilled researchers, and training initiatives remained largely voluntary and unstructured.

Organizational culture and structure further shaped AI integration. I.5 noted that smaller, agile startups often adopt AI more quickly, while larger, bureaucratic organizations face slower progress due to internal complexity, policies, and experimental integration approaches. I.4 stressed that many organizations are still learning how to implement AI strategically and ethically, while I.2 described a "submerged iceberg" phenomenon, where organizations understand surface-level AI capabilities but remain unaware of deeper, transformative applications.

The empirical data also validated the sustainability paradox of AI. I.4 illustrated this through the "Stargate" project in Texas, a large-scale data center initiative by OpenAI and its partners, projected to require approximately 15 terawatts of energy capacity, comparable to the energy consumption of major global cities such as New York, Paris, or Tokyo. This suggests that AI infrastructure is not only a business asset but also a global resource competitor. I.1 added that the issue extends beyond electricity, as HVAC and refrigeration systems for large data processing units create significant water footprints, a critical bottleneck often overlooked in sustainability discussions.

In summary, internal AI integration is enabled by financial investment, technical infrastructure, high-quality data, internal expertise, and employee training. However, it is hindered by high implementation costs, legacy-system integration, poor data quality, AI hallucinations, limited strategic expertise, and workforce resistance. Human capital readiness depends on structured upskilling, while sustainability concerns show that AI adoption must be assessed not only as a technological or business decision, but also as a resource-intensive environmental challenge.

### Business external environment - responding to market and regulatory pressures

This subsection addresses RQ3 by exploring how market expectations, competitive pressure, customer needs, and regulatory frameworks shape organizational strategies for balancing AI-driven efficiency with environmental and social responsibility.

The interviews show that organizations are increasingly pressured by market expectations and regulatory frameworks to adopt AI, with direct implications for competitiveness, operational efficiency, and sustainability. Across sectors, AI is no longer perceived as optional, but as a strategic necessity in an evolving business environment.

Experts consistently identified market demand as a key driver. I.1 noted that both business-to-business (B2B) and business-to-consumer (B2C) customers increasingly expect AI-driven solutions. Organizations that fail to adopt AI risk losing competitive advantage, as AI enables innovation, efficiency, and improved products and services. I.4 similarly highlighted AI's role in personalization, efficiency, and identifying emerging market gaps, while stressing that human decision-making remains essential for acting on these insights. I.5 discussed AI's value in sales, marketing, and customer engagement, especially in smaller-scale applications, but noted that larger, regulated sectors adopt AI more slowly due to compliance and traceability requirements. I.2 added that tools such as Generative Engine Optimization (GEO) are transforming digital marketing by requiring firms to optimize not only for human consumers but also for AI systems that increasingly influence customer traffic. I.3

emphasized that although higher education institutions recognize AI's potential for efficiency and competitiveness, adoption remains early-stage, with processes and roles still evolving.

Regulatory pressures act as both enablers and barriers. I.1 observed that while regions such as the EU have developed AI regulations, many countries, including emerging economies, still lack robust AI frameworks, creating challenges for ethical adoption and data governance. I.4 and I.5 similarly noted that inconsistent or underdeveloped regulation creates uncertainty, while governmental financial support remains limited. I.2 and I.3 described the EU AI Act as an important milestone in human-centric AI governance, but warned that overly restrictive regulation could slow innovation and discourage foreign direct investment. Across interviews, data privacy, traceability, and auditability were repeatedly identified as critical compliance concerns, especially in regulated sectors.

Although some governmental incentives exist, experts agreed that organizations often need to self-fund AI adoption. I.1 and I.4 emphasized the importance of prioritizing AI deployment in high-impact areas under budget constraints. I.5 highlighted localized, site-specific AI solutions as more manageable and cost-effective sustainability interventions than large centralized projects. I.2 added that although AI's initial energy consumption is high, its long-term application may generate sustainability efficiencies, aligning with the Kuznets curve logic, where technological maturity eventually reduces environmental impact.

In summary, market and regulatory pressures jointly shape AI adoption. Market demand encourages innovation, efficiency, personalization, and customer engagement, while regulation defines the boundaries for ethical, accountable, and legally compliant AI use. However, successful adoption depends on balancing competitiveness, compliance, technological capability, workforce readiness, financial investment, data quality, and targeted deployment. The findings suggest that AI's sustainability potential is strongest when organizations use it strategically in high-value areas while managing its regulatory, ethical, and environmental constraints.

## Managerial implications

For managers, the discussion highlights that AI should not be viewed solely as a tool for boosting operational efficiency but as a technology with significant sustainability trade-offs. While AI can optimize energy use, improve forecasting, and enhance decision-making, it simultaneously increases energy consumption, water usage, and hardware-related emissions. Managers must therefore adopt a dual approach: capturing the performance benefits of AI while actively mitigating its environmental footprint. This requires evaluating the lifecycle impact of AI systems, choosing appropriately scaled models, and integrating renewable energy and efficient data-center solutions into digital strategies.

The text underscores that successful AI adoption depends not just on technology, but on organizational readiness, workforce capability, and ethical governance. Managers must prioritize skill development, cross-functional collaboration, and transparent governance frameworks to ensure responsible and sustainable AI use. This includes aligning AI initiatives with Corporate Social Responsibility, establishing policies for data quality, privacy, and fairness, and ensuring employees are supported through reskilling and change-management processes. Doing so helps managers avoid resistance, reduce implementation risks, and improve stakeholder trust.

Managers can leverage insights from the literature to understand that AI becomes most valuable when strategically deployed to support broader organizational and sustainability objectives, rather than being adopted opportunistically. AI can strengthen green innovation, improve ESG reporting, enhance supply-chain transparency, and support circular-economy initiatives. By integrating AI within sustainability strategies through predictive monitoring, smart resource management, and data-driven environmental decision-making, managers can enhance long-term resilience and contribute to the Triple Bottom Line. This positions the company not only for economic benefits, but also for improved environmental and social performance.

To address the long-term environmental viability of AI, this study proposes the application of the Environmental Kuznets Curve (EKC) theory to digital transformation. According to Expert I.4, AI is currently at the beginning of the industrialization slope, where its negative environmental impact is at its peak due to high energy and resource consumption. However, the model suggests that as AI technology matures and reaches a high level of integration, it will identify systemic efficiencies that reverse the curve, eventually leading to net-positive environmental outcomes. For decision makers, this implies that the focus should not be on halting AI adoption due to its initial footprint, but on accelerating the transition through the curve by incentivizing 'Green AI' architectures and mandatory resource disclosure. This perspective transforms the sustainability challenge from a static 'energy problem' into a dynamic 'efficiency transition'

## Theoretical implications

This study offers significant theoretical value by deepening academic understanding of the dual role of Artificial Intelligence in organizational efficiency and sustainability performance. By synthesizing evidence on AI's ability to enhance predictive analytics, resource optimization, and environmental monitoring, the text advances theoretical discourse on how digital technologies function as socio-technical systems rather than purely operational tools. For researchers, this duality highlights the need to conceptualize AI not only as an enabler of sustainability but also as a generator of new ecological pressures due to its energy, water, and hardware demands. This creates an important theoretical tension that invites further investigation into the trade-offs, systemic feedback loops, and boundary conditions that determine when AI produces net-positive sustainability outcomes.

Furthermore, the text contributes to theoretical frameworks that examine technology adoption, particularly the TOE and Triple Bottom Line models. By integrating these models with ethical and ESG considerations, the analysis extends traditional theoretical boundaries and encourages scholars to adopt a more holistic lens when assessing digital transformation. The work suggests that AI adoption cannot be fully explained by technological readiness alone; instead, it requires a multidimensional understanding of governance, social responsibility, circularity, and organizational learning. This expanded theoretical framing supports the development of more robust models that capture the interplay between digital innovation, sustainability strategies, and organizational capability building.

Finally, the text enriches academic discussions on responsible AI governance by linking AI-driven transformation with emerging sustainability demands and human-centered organizational dynamics. Researchers studying ethical AI, sustainability transitions, or organizational adaptation can draw on these insights to develop new theories about how firms navigate technological ambiguity, regulatory constraints, and societal expectations. By positioning AI at the intersection of economic performance, environmental stewardship, and employee well-being, the text provides a comprehensive foundation for future theoretical work exploring how advanced technologies shape systemic sustainability outcomes across industries and contexts.

## Limitations of research

This study has several limitations. First, the empirical scope is narrow, as the findings are based on semi-structured interviews with a small group of experts. Although participants had relevant experience in AI, sustainability, and ESG governance, their views cannot be generalized across all industries, regions, or organizational maturity levels. A further limitation concerns the use of LinkedIn as the primary channel for identifying interviewees. Although participants were screened based on professional experience, expertise, and relevance to the research topic, LinkedIn-based recruitment may still introduce selection bias. It may favor more visible professionals, individuals active on the platform, or those whose expertise is more explicitly presented in public profiles.

Second, AI technologies and sustainability regulations are evolving rapidly. Therefore, the findings represent a specific moment in time and may change as AI systems become more efficient, regulatory frameworks mature, and organizational governance practices develop.

Third, the study relies partly on expert perceptions rather than measured environmental or operational data. Many organizations still lack complete information on AI-related energy use, resource consumption, ROI, or employee outcomes. Future research should therefore incorporate quantitative environmental metrics, longitudinal data, and additional organizational variables such as workforce demographics, digital maturity, and sector-specific adoption patterns.

## Summary

Artificial Intelligence plays a dual role in contemporary organizations, acting as both a powerful enabler of sustainability and a source of new environmental pressures. On one hand, AI enhances operational efficiency, predictive analytics, and resource optimization, enabling firms to reduce energy consumption, minimize waste, and support resilient systems aligned with the Sustainable Development Goals. Its integration with complementary technologies such as the Internet of Things and Distributed Ledger Technology further strengthens data-driven decision-making, promotes green innovation, and supports decentralized, low-carbon energy systems.

However, AI adoption is not without challenges. Technology itself consumes significant energy, relies on resource-intensive hardware, and contributes to water use and electronic waste, creating a sustainability paradox. The interviews with AI experts highlighted that these environmental costs, combined with high implementation complexity, workforce readiness issues, and regulatory constraints, often limit the net sustainability benefits of AI. Experts noted that while AI improves operational performance and ESG reporting, tangible benefits for employee well-being and environmental outcomes are highly dependent on organizational maturity, sector context, and targeted deployment strategies.

Interviewees emphasized several internal and external enablers for effective AI adoption. Financial and technical readiness, high-quality data, and employee training emerged as key internal factors, while market demand and regulatory pressures acted as external drivers. Conversely, barriers such as high costs, workforce resistance, data limitations, and inconsistent regulations hinder AI integration. Strategic implementation, coupled with ethical governance, organizational learning, and alignment with sustainability objectives, was repeatedly identified as crucial to unlocking AI's full potential for the Triple Bottom Line: economic, environmental, and social performance.

Overall, AI presents a complex trade-off: it is a transformative tool that can advance sustainable business practices, yet its deployment requires careful management of environmental and social impacts. Organizations that adopt AI strategically, integrate supportive governance frameworks, and prioritize workforce readiness are best positioned to leverage its benefits while mitigating potential negative consequences. The study underscores the need for ongoing research into context-specific strategies, policy frameworks, and measurement approaches to ensure AI contribute positively to long-term sustainability.

During the preparation of this work the author(s) used [ChatGpt and Quillbot] in order to [Citation check, fluency, and guideline check]. After using this tool/service, the author(s) reviewed and edited the content as needed and take(s) full responsibility for the content of the publication.

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## Appendices

### Appendix 1 Interview questions

1. Based on your experience, how has the introduction of AI technologies changed organizational operations in terms of employee well-being and inclusion, business performance and competitiveness, and environmental efficiency or sustainability?
2. Based on your experience, in what ways are organizations technologically and financially prepared to adopt AI responsibly, while ensuring employee readiness, sustainable investment, and consideration of environmental impacts such as energy use or e-waste?
3. Based on your experience, how do organizations prepare and support employees for AI-driven change, for example socially through trust and inclusion, economically through skill development and productivity gains, and environmentally through awareness of sustainable technology use?
4. Based on your experience, how do internal support functions such as HR, IT, or finance enable the ethical, financially responsible, and environmentally conscious integration of AI across organizations?
5. Based on your experience, how is AI integrated into organizations' main activities in ways that enhance customer relationships and social value, improve operational and economic performance, and contribute to environmental goals such as efficiency or waste reduction?
6. Based on your experience, how do AI-driven market trends create opportunities for organizations to promote social inclusion, generate sustainable economic growth, and develop environmentally friendly products or services?
7. Based on your experience, how does competition influence organizations' approach to AI adoption in terms of social responsibility, economic resilience, and environmental performance?
8. Based on your experience, how are evolving customer expectations around ethics, affordability, and environmental responsibility shaping the way organizations design and deliver AI-enabled products or services?
9. Based on your experience, how do government policies, incentives, or regulations affect organizations' ability to implement AI in a socially responsible, economically sustainable, and environmentally conscious manner?