From Self-Perception to Reality in Digital Competence: Findings from the DigComp 2.2 Framework

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Abstract: The rapid expansion of digital technologies in higher education has revealed persistent discrepancies between self-perception and actual performance in digital skills. Self-assessment of digital competence is notoriously unreliable, often masking critical skill gaps by conflating confidence with actual competence. This study, involving 629 military university students, introduces an alternative methodology designed to overcome the limitations of simple self-perception measures. Results from the DigComp 2.2 framework were used to validate two complementary constructs: (1) the Response Consistency Index (RCI), a promising proxy for metacognitive self-awareness, and (2) the Digital Readiness Index (DRI), a second-order latent model built using Confirmatory Factor Analysis within a Structural Equation Modelling framework that integrates the RCI with perceived competences and objective performance. The findings confirm significant discrepancies between perception and competence, identifying profiles consistent with over- and underconfidence (also known as the Dunning–Kruger effect). Additionally, Problem Solving and Information and Data Literacy are identified as the most deficient domains—a weakness observed even in the highest-performing students. The evidence from this study strengthens the idea that digital readiness is not simply the possession of skills, but rather the intersection of competence and accurate self-awareness of that competence. In the era of artificial intelligence, this emphasises the need for precise educational diagnosis and pedagogical intervention to overcome the illusion of digital competence generated by mere self-reports. By providing instructors and instructional designers with diagnostic tools that go beyond declared competence, this approach contributes directly to the advancement of evidence-based, adaptive e-learning practice. The proposed framework supports the development of learning analytics dashboards and pedagogical interventions that respond not only to what students know, but to how accurately they perceive what they know. These validated instruments—the RCI and the DRI—can directly inform the design of adaptive e-learning interventions and personalised digital training pathways in higher education contexts.

Keywords: Digital competence, DigComp 2.2, Response Consistency Index (RCI), Digital Readiness Index (DRI), Dunning-Kruger effect, Metacognitive calibration

1. Introduction

The European Digital Competence Framework for Citizens (DigComp) is a popular initiative of the European Commission aimed at defining and assessing essential digital competences in the current technological landscape. Since its inception in 2013 and subsequent updates culminating in version 2.2 (2022), DigComp has become a widely adopted reference framework across multiple contexts. Digital competence is defined as the knowledge, skills, and experience required to understand, evaluate, implement, and promote digital technologies (Chen, Ebrahimi and Cheng, 2025). As such, DigComp has served as a foundational standard for the development and evaluation of digital competence within and beyond Europe (Balyk et al., 2019; Bartolomé et al., 2025; Cabezas-González, Casillas-Martín and García-Valcárcel, 2024). Despite the emergence of alternative approaches—such as using learning analytics for competence assessment (Guallichico et al., 2023) or developing new evaluation tools (Tarazona Gil, Lloret Català and Martínez-Usarralde, 2025)—DigComp 2.2 remains one of the most widely adopted and relevant frameworks.

1.1 Advantages of the DigComp 2.2 Framework

DigComp 2.2 offers a robust, adaptable framework for fostering digital competence across diverse sectors and populations. One of its key strengths lies in its comprehensive and flexible design, which supports the development of digital skills among citizens across a broad range of contexts—including both personal and

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professional spheres (Al Khateeb, 2017). Its structure enables implementation in multiple domains, such as education, healthcare, and the architecture, engineering, and construction (AEC) industry (AlDhaen, 2025; Chen, Ebrahimi and Cheng, 2025).

In the educational domain, DigCompEdu—a specialised adaptation of the DigComp framework—has received positive evaluations for its emphasis on pedagogical application. Unlike other frameworks that primarily focus on technological proficiency, DigCompEdu integrates pedagogical dimensions, aiding in the identification of training needs and enabling the design of personalised professional development paths (Cabero-Almenara et al., 2021; Gabbi and Ancillotti, 2024; Gutiérrez-Castillo et al., 2023).

A core principle of DigComp is its promotion of lifelong learning and continuous self-development. It underscores the importance of not only updating one's own digital skills but also supporting others in the acquisition of these competences (Biggins, Holley and Zezulkova, 2017). The inclusion of updated dimensions such as data literacy, collaborative work, and enhanced cybersecurity in versions 2.1 and 2.2 reflects an awareness of increasingly complex digital environments and growing concerns related to privacy, safety, and digital well-being (Calero-Plaza, González-García and Fernández-Piqueras, 2025).

Furthermore, DigComp has provided a validated foundation for the development of reliable assessment instruments. Tools such as the "ECODIES" questionnaire for students and the "DigCompEdu Check-In" for educators demonstrate strong psychometric properties and practical utility (Betín de la Hoz et al., 2023; Casillas Martín, Cabezas González and García Peñalvo, 2020; Ergül and Taşar, 2023). These instruments play a critical role in diagnosing levels of digital competence and informing data-driven educational policy and planning (Casillas Martín, Cabezas González and García Peñalvo, 2020).

1.2 Disadvantages and Limitations of the DigComp 2.2 Framework

Despite its many benefits, DigComp 2.2 and its associated instruments have several limitations that warrant critical attention. One of the most prominent issues is the discrepancy between individuals' self-perception of digital competence and their actual performance (González-Mujico, 2024). While tools such as the DigCompEdu Check-In have demonstrated validity and reliability in measuring self-perceived competence (Cabero-Almenara et al., 2021), self-assessments often diverge from observable behaviours and real-world application (González-Mujico, 2024).

Overestimation of digital competence is a recurring concern. Many individuals tend to rate their abilities higher than they are in practice (Martzoukou et al., 2020; Marzan, Stamate and Spiru 2024, Momdjian, Manegre and Gutiérrez-Colón, 2025; Vuorikari, Pokropek and Muñoz, 2025). Empirical studies indicate that approximately 30% of participants overrate their skills, while up to 68% may perform ineffective or superficial actions intended to demonstrate competence (Muszyński et al., 2023). Conversely, underestimation—though less frequent—also occurs, particularly among older adults or highly experienced educators who may underestimate their digital fluency due to lack of confidence or changing standards (Liesa-Orus, Blasco and Arce-Romeral, 2023; Marzan, Stamate and Spiru, 2024; Schwarz et al., 2024).

These distortions contribute to what has been termed an "explanatory gap"—a mismatch between reported competence and actual capability—that cannot be adequately captured through self-report methods alone (Bartolomé et al., 2025; González-Mujico, 2024). This gap is further compounded by the Dunning–Kruger effect, a well-documented cognitive bias in which individuals with lower competence tend to significantly overestimate their abilities (Dunning, 2011). In such cases, low-performing individuals may believe they are above average, thereby reducing their motivation to seek training or support (Golz, Hahn and Zwakhalen, 2024; Schlösser et al., 2013).

Moreover, self-reporting is inherently prone to response biases, particularly social desirability bias, which can compromise data accuracy (Amin et al., 2025). Participants may respond in ways they believe are expected or socially acceptable rather than providing honest assessments of their actual skills, leading to inflated scores and potentially flawed conclusions (Montenegro-Rueda and Fernández-Batanero, 2024; Vuorikari, Pokropek and Muñoz, 2025).

Memory inaccuracies and recall errors further undermine the reliability of self-assessed data (Benaoui and Kassimi, 2021). Correlations between self-reports and objective cognitive performance measures have been found to vary widely—from as low as $r = 0.2$ to as high as $r = 0.8$—suggesting that while some self-assessments may be indicative of actual competence, others offer only a vague approximation (Muszyński et al., 2023).

1.3 Additional Research Gaps

A review of the current literature reveals other critical gaps that must be addressed to achieve a more complete understanding and more effective implementation of digital competence:

Validation beyond self-assessment: Much of the existing research relies heavily on self-perception as a measure of digital competence. However, this approach presents well-documented limitations, particularly in aligning perceived versus actual skill levels (González-Mujico, 2024). There is a clear need for more empirical studies that validate DigComp through direct assessment methods, such as structured classroom observation or task-based performance analysis. Comparing self-perceived competence with objectively measured performance can offer deeper insights into digital proficiency and help refine theoretical constructs in the field (González-Mujico, 2024).

Specific studies by population groups: While DigComp is designed as a flexible, overarching framework, more targeted studies are needed to address the unique contexts of specific user groups. For instance, older adults (Calero-Plaza, González-García and Fernández-Piqueras, 2025), nurses (Buhagiar, 2023; Golz, Hahn and Zwakhalen, 2024), trainee teachers (Lázaro-Cantabrana, Usart-Rodríguez and Gisbert-Cervera, 2019; Grande-de-Prado et al., 2020; Jogezai, Koroleva and Baloch, 2023), and healthcare professionals (AlDhaen, 2025; Karvouniari et al., 2024) face distinctive digital demands and challenges. Focused research could facilitate the development of adapted tools and strategies that better serve these communities.

Longitudinal and organisational studies: Another gap concerns the lack of longitudinal studies and organisational case studies that track digital transformation over time. Quantitative research that identifies both enablers and barriers to digital competence acquisition remains scarce (Chen, Ebrahimi and Cheng, 2025). Furthermore, investigations into how institutional culture and leadership affect digital adoption could offer valuable insights, particularly when studied within high-performing or digitally mature organisations. The same is true of linguistic and cultural contexts (Díaz-Burgos et al., 2024).

Based on the identified gaps, this study examines the discrepancy between self-perceived and actual digital competence by validating the Response Consistency Index (RCI) as a proxy for metacognitive self-awareness. The RCI is integrated into a composite Digital Readiness Index (DRI), which is applied to a cohort of military students to assess the reliability of self-assessment and its implications for targeted digital skills development.

1.4 Research Questions

Based on the identified gaps in the literature, this study addresses the following research questions:

RQ1: To what extent do self-assessed digital competence scores align with objective performance outcomes among military university students, and to what extent can the Response Consistency Index (RCI) serve as a reliable proxy for metacognitive self-awareness?

RQ2: Which specific DigComp 2.2 competence domains exhibit the greatest discrepancy between self-perception and actual competence, and are these discrepancies consistent across different performance levels?

RQ3: Can the Digital Readiness Index (DRI), a composite construct integrating perceived competence, response consistency, and objective performance, provide a more accurate and psychometrically robust assessment of digital readiness than traditional self-report measures alone?

2. Materials and Methods

This study employed a quantitative descriptive-analytical design. Ethical approval for this study was granted by the Joint Command of the Armed Forces in Ecuador as part of an approved institutional research project.

The study population comprised 629 military university students (mean age = 20.1 years). Participation was voluntary, and all respondents were enrolled in military academic programmes at the undergraduate level.

To assess digital competence, the DigComp 2.2 digital skills test was administered (Vuorikari, Kluzer and Punie, 2022). The instrument was developed based on the 21 competence areas outlined in the European Digital Competence Framework for Citizens, grouped into five core domains: information and data literacy, communication and collaboration, digital content creation, safety and problem solving. The test items were structured using a 4-point Likert scale, with response options ranging from: “Never” (1), “Sometimes” (2), “Almost always” (3), “Always” (4).

Each survey item was derived directly from the competence descriptors and proficiency-level examples published in the official DigComp 2.2 framework (Vuorikari, Kluzer and Punie, 2022). The instrument was adapted to the military higher education context through a pilot study with 45 students from the same institution, after which minor linguistic adjustments were made to improve clarity without altering the underlying competence constructs. Face and content validity were reviewed by a panel of three experts in digital education and one expert in military training, confirming adequate alignment between the items and the original DigComp descriptors.

These responses were used for statistical analysis and enabled the calculation of an RCI for each participant. The RCI evaluates the internal consistency of responses within each DigComp domain, calculated based on the intra-domain standard deviation. An RCI value approaching 1.0 indicates high consistency, whereas lower values (closer to 0) suggest potential contradictions, random answering patterns, or inflated self-assessments. Cases with RCI < 0.5 or RCI = 1.0 (indicative of extreme response behaviour) were flagged for further analysis. Based on these data, a DRI was developed which integrates both the self-reported competence level and the RCI, thereby weighting participants' reported skill levels by the internal consistency of their responses.

Following the diagnostic phase, a performance-based test was administered to contrast self-perception with reality. This instrument consisted of 3 tasks per item aligned with the examples of knowledge, skills, and attitudes specified in DigComp 2.2. This test served as a benchmark for actual digital competence, enabling comparison between self-perceived ability and demonstrated performance. Scoring was binary (1 = Correct, 0 = Incorrect) to minimize subjective interpretation. This objective score (C_obj) was used to calculate the Discrepancy Index (DI) as explained in section 2.1.3 Phase 3.

The performance-based test comprised 63 tasks (three per each of the 21 DigComp 2.2 competence areas) and was designed following the examples of knowledge, skills, and attitudes provided in the official DigComp 2.2 documentation (Vuorikari, Kluzer and Punie, 2022). Tasks included, for example, identifying a phishing email (Safety), selecting the most efficient search operator (Information Literacy), and troubleshooting a file-format compatibility issue (Problem Solving). Content validity was established through expert review by three digital education specialists, who rated each task for alignment with its target competence descriptor using a relevance scale. Inter-rater scoring reliability was assessed on a random subsample of 60 responses, yielding a Cohen's kappa of $\kappa = 0.91$, indicating near-perfect agreement. The binary scoring protocol was adopted to eliminate subjective interpretation and to maximise comparability with the Likert-based self-assessment instrument.

2.1 Procedure

Following data collection and preprocessing, internal consistency of the DigComp 2.2 instrument was assessed using Cronbach's Alpha (α). The results indicated that 17 out of 21 competence domains achieved an alpha value of $\alpha \geq 0.70$, suggesting an acceptable level of reliability for the majority of the instrument. However, certain domains exhibited lower internal consistency and warranted further scrutiny. Specifically, Domain 1.1 (Navigation and Search) yielded an alpha of $\alpha = 0.53$, indicating poor reliability. Additionally, Domain 1.3 (Data Management) and Domain 4.3 (Health Protection) recorded values of $\alpha = 0.69$ and $\alpha = 0.63$ respectively, falling into the range of questionable consistency. While previous studies have reported significantly higher internal reliability using DigComp-based instruments (Zhao et al., 2021, $\alpha = 0.978$), contextual and sample-specific factors may explain these discrepancies. In response to these initial findings, the data analysis was structured into four sequential phases to ensure methodological rigour and address potential reliability concerns.

The lower reliability observed in Domains 1.1, 1.3, and 4.3 may reflect the heterogeneous nature of the skills assessed within these areas and the limited number of items per domain, which is a known constraint in short-scale instruments (Taber, 2018). To mitigate potential bias, sensitivity analyses were conducted excluding these domains; results remained substantively unchanged, confirming that the overall pattern of findings is robust. Nevertheless, these reliability limitations are acknowledged as a constraint of the current instrument and are considered when interpreting domain-level results for Navigation and Search, Data Management, and Health Protection.

To facilitate the reader's comprehension of the overall analytical workflow, Figure 1 provides a schematic overview of the four-phase procedure. Each phase builds upon the outputs of the preceding one: Phase 1 computes the RCI from the self-assessment instrument; Phase 2 examines the relationship between RCI and domain scores through correlation and regression analyses; Phase 3 introduces the performance-based test to calculate the Discrepancy Index (DI) and detect the confidence–competence paradox; and Phase 4 integrates all prior metrics into the DRI through CFA/SEM modelling. This sequential design ensures that each analytical layer is grounded in validated prior results before contributing to the composite readiness model.

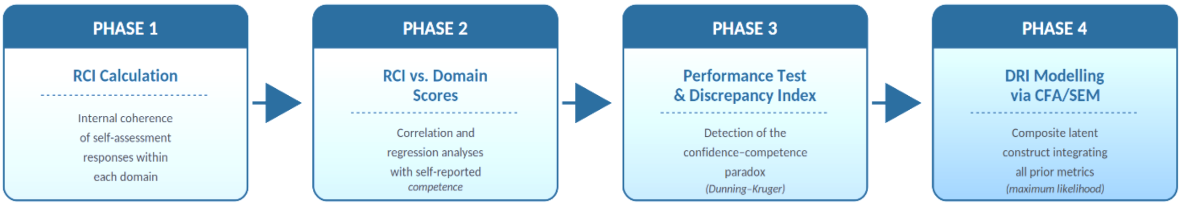

Figure 1: Schematic overview of the four-phase analytical procedure

Before detailing each phase, it is important to clarify the conceptual relationships among the three derived indicators. The RCI captures the internal coherence of self-assessment responses within each domain, serving as a reliability qualifier of self-reported data. The DI quantifies the direction and magnitude of the gap between self-perception and objective performance, identifying over- or underconfidence. The DRI is the integrative construct that synthesises both: it weights perceived competence by its consistency (RCI) and adjusts for systematic perception biases (DI), producing a single composite score that reflects not merely what students believe they can do, but how reliably and accurately they hold those beliefs. In this architecture, the RCI and DI are diagnostic inputs, while the DRI is the latent outcome.

2.1.1 Phase 1: Response Consistency Index (RCI)

In the first phase of analysis, an RCI was calculated for each participant to assess the internal coherence of responses within individual DigComp 2.2 domains. The RCI serves as a proxy indicator of metacognitive self-awareness, reflecting the degree to which respondents provide consistent answers to semantically similar or conceptually related items. To operationalise the RCI, inverse and redundant item pairs were identified within each domain. For example, one item might assess “confidence in using digital tools,” while its inverse measures hesitancy or avoidance of similar tools. These pairings allowed for the detection of internal response contradictions that may suggest random guessing, misinterpretation, or inflated self-assessment.

The interpretation of response consistency as a proxy for metacognitive self-awareness is grounded in the theoretical framework of metacognitive monitoring (Flavell, 1979; Kruger and Dunning, 1999). Metacognitive calibration refers to the accuracy with which individuals judge their own cognitive performance. When a respondent provides internally consistent answers across semantically related items, this signals a coherent self-model of competence, which constitutes a behavioral indicator of effective metacognitive monitoring. Conversely, inconsistent responses to conceptually equivalent items suggest either a fragmented self-representation or a lack of reflective engagement with the assessment. The RCI thus operationalises the degree of internal coherence in self-evaluation, which prior research has identified as a behavioural correlate of metacognitive accuracy (Schlösser et al., 2013).

The RCI was computed as the mean absolute deviation between participants’ actual responses and the expected pattern of internally consistent answers. Scores were then normalised on a continuous scale from 0 to 1, where:

RCI ≈ 1.0 indicates high response consistency, suggesting thoughtful and reliable self-assessment,

RCI < 0.5 reflects low consistency, potentially due to confusion, disengagement, or response bias,

RCI > 0.9 was used to identify participants with highly stable responses, who may serve as internal benchmarks or models of competence.

This index was not only used as a filtering criterion in data quality assurance but also integrated into the DRI in subsequent phases to weight self-assessment scores by response reliability.

2.1.2 Phase 2: Comparison of RCI indices with domain scores

In the second phase, RCI values were compared with domain scores derived from the DigComp 2.2 self-assessment instrument. Domain scores were calculated by computing the arithmetic mean of participant responses for each of the five competence areas. This enabled an aggregated measure of self-perceived proficiency within each domain. Although geometric aggregation is a commonly adopted option in the construction of composite indices—precisely because it strongly penalises imbalances among dimensions by following a non-compensatory logic (i.e., weaknesses in one domain cannot be fully counteracted by strengths in others)—this study intentionally chooses the arithmetic mean (AM) as the aggregation method. This choice is grounded in two key arguments that reinforce its theoretical and methodological appropriateness.

First, the DigComp 2.2 framework treats digital competences as clearly differentiated domains that are, nevertheless, positively correlated. That is, progress in one domain tends to facilitate or reinforce progress in others, thereby supporting a compensatory logic: strengths in certain domains can, to some extent, compensate for weaknesses in others without disregarding the importance of balanced development across all domains.

Second, the use of the AM maintains strong coherence with the structural equation modelling (SEM) approach employed in this study. In our proposed SEM framework, domain scores are treated as continuous indicators of a higher-order latent construct representing overall digital competence. Furthermore, this practice aligns with established psychometric standards for the aggregation of items or domains assessed via Likert scales in the field of competences (Vuorikari, Kluzer and Punie, 2022), thereby avoiding potential distortions that non-linear methods, such as geometric aggregation, might introduce in contexts where indicators reflect a common latent dimension.

To examine the relationship between response consistency and self-assessed competence, Pearson correlation analyses were conducted. Additionally, to control for the potential influence of demographic variables—including age, gender, and educational level—multiple linear regression models were applied. This allowed for a more nuanced interpretation of the association between RCI and self-reported domain scores, accounting for individual differences in participant profiles.

This phase aimed to determine whether higher response consistency (as measured by RCI) correlated with higher self-assessed competence, and whether this relationship held when controlling for relevant sociodemographic factors.

2.1.3 Phase 3: Detection of the confidence versus competence paradox

The third phase focused on identifying the confidence–competence paradox, a phenomenon closely associated with the Dunning–Kruger effect—a cognitive bias whereby individuals with lower ability levels tend to overestimate their competence, while more proficient individuals may underestimate their own skills (Kruger and Dunning, 1999).

This paradox was detected by measuring the discrepancy between self-perceived competence (subjective scores on confidence items) and objective competence (scores on knowledge and practical skills items). A Discrepancy Index (DI) was calculated for each participant to quantify the gap between self-perceived and actual competence levels:

$$DI_i = \sum (C_{sub} - C_{obj}) / \max(C_{sub}) - \min(C_{obj})$$

Where C_sub is subjective confidence and C_obj is objective competence. Positive DI values indicate overconfidence (paradox present), while negative values suggest underconfidence.

The DI served as a diagnostic metric to categorise individuals as: overestimators (high self-assessment, low performance), underestimators (low self-assessment, high performance) or accurate estimators (alignment between self-perception and actual competence). The DI enabled a detailed analysis of metacognitive accuracy across the sample and contributed to the overall construction of the DRI in the subsequent phase.

2.1.4 Phase 4: Modelling the Digital Readiness Index (DRI)

In the final phase, the DRI was conceptualised and modelled as a second-order composite construct that integrates the findings from the previous phases. To develop the DRI, a Confirmatory Factor Analysis (CFA) was conducted within a Structural Equation Modelling (SEM) framework using IBM SPSS AMOS software. CFA was employed to verify the underlying factor structure, specifically how the observed variables (i.e., test items) load onto latent constructs representing the five core DigComp 2.2 domains.

The DRI was operationalised as a second-order latent factor, derived from the five first-order latent variables corresponding to the five main areas of DigComp 2.2: Information and Data Literacy, Communication and Collaboration, Digital Content Creation, Safety, Problem Solving.

To account for response inconsistencies and cognitive biases observed in earlier phases, the model incorporated two weighting mechanisms: the RCI, which quantified the internal reliability of each participant's self-assessment using intra-domain standard deviation and, where applicable, serial correlation coefficients; and the Discrepancy Index (DI), which measured the divergence between self-reported competence and performance-based outcomes, capturing overestimation or underestimation effects consistent with the Dunning–Kruger bias. These indices were integrated into the model through adjusted factor loadings, ensuring that each domain's contribution to the DRI reflected not only perceived skill levels but also the internal consistency and metacognitive accuracy of each respondent's self-assessment. This approach allowed the DRI to more accurately represent digital readiness while correcting for known distortions in self-report data.

Specifically, the integration of RCI and DI into the SEM model followed a two-step approach. First, each participant's raw domain score was multiplied by their domain-specific RCI value, producing a consistency-adjusted competence score. This multiplicative weighting ensures that high self-reported scores accompanied by low response consistency are penalised proportionally. Second, the DI was incorporated as an observed covariate in the structural model, allowing the CFA to partial out the variance attributable to systematic overestimation or underestimation. The DRI was then estimated as the second-order latent factor from the five consistency-adjusted domain scores, with the DI informing the error structure. All model parameters—including factor loadings, residual variances, and second-order path coefficients—were estimated simultaneously via maximum likelihood in AMOS.

The model's fit was evaluated using widely accepted psychometric and SEM fit indices (Hu and Bentler, 1999):

Comparative Fit Index (CFI): Values above 0.95 were required to indicate excellent model fit relative to a null model.

Root Mean Square Error of Approximation (RMSEA): A value below 0.06, with 90% confidence intervals, denoted acceptable fit and accounted for model complexity.

Standardized Root Mean Square Residual (SRMR): Values under 0.08 were interpreted as evidence of limited misspecification and strong absolute model fit.

All fit statistics met or exceeded the recommended thresholds, with the final model yielding (CFI > 0.95, RMSEA < 0.05, SRMR < 0.06), indicating a robust fit between the hypothesized model and the empirical data. Furthermore, standardized factor loadings were all greater than 0.70, supporting convergent validity, while composite reliability (CR) values exceeded 0.80 across all domains. Discriminant validity was confirmed using the Fornell–Larcker criterion, verifying the distinctiveness of each latent construct within the model. These procedures contribute to the broader body of research on digital competency frameworks by integrating metacognitive self-awareness and psychometric robustness into a unified readiness model.

3. Results

Once the data has been processed using the DigComp 2.2 framework metrics and the RCI has been calculated, the results obtained are presented below. These are organized by competence domains, performance levels, and consistency patterns, allowing for a comprehensive analysis of the participants' digital skills.

3.1 Response Consistency Index (RCI) Results

Figure 2 presents the distribution of the Response Consistency Index (RCI) across the 629 participants. The following observations can be drawn from the histogram:

1. The horizontal axis (X-axis) shows the RCI, where 0 = maximum inconsistency and 1 = perfect consistency.
2. Vertical axis (Y axis) shows how many individuals fell into each RCI range. Higher bars mean more people in that consistency range. The peak of the histogram is around RCI = 0.70 to 0.85, suggesting that most respondents were fairly consistent, though not perfect.
3. This means that, while many people were fairly consistent, a few achieved a very high RCI (close to 1), but not the majority. An RCI of 1.0 indicates that the respondent gave exactly the same answer (e.g., all "Always" or all "Almost always") to every question within each domain (Information Literacy, Security, etc.).

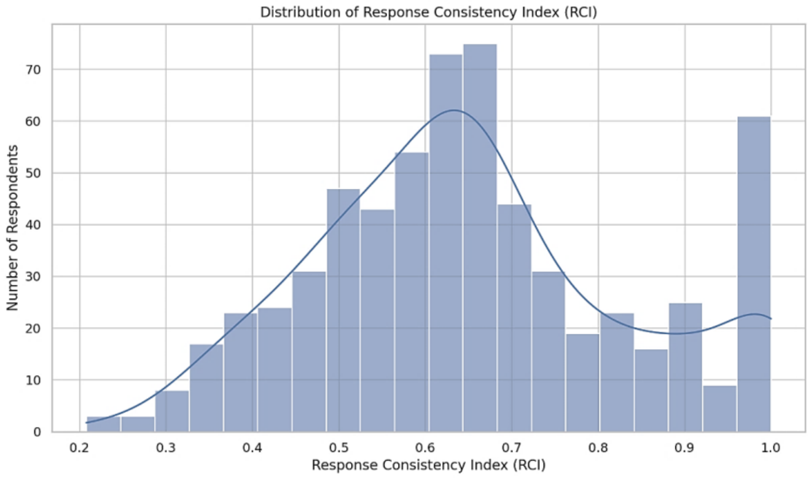

Figure 2: Distribution of Response Consistency Index (RCI)

As Fig. 2 shows, the RCI values are distributed fairly symmetrically, but slightly skewed to the right (with a tail toward 1.0). Potential scenarios and implications of extreme RCI values are discussed in the Discussion section.

3.2 RCI Scores Versus Domain Scores

The scatter plots shown in Figure 3 visualize the relationship between the RCI and the average score for each of the five digital competence domains. Each point represents one respondent. Analysis of these scatter plots reveals the following trends:

Information and data literacy: Fig 3 (A) shows a slight upward trend in RCI scores in relation to information and data literacy. Greater consistency tends to align with higher literacy scores: those who are more reflective about their information-seeking habits (e.g., verifying sources) tend to be more consistent. Some respondents with low RCI also scored high, suggesting possible overestimation or selective understanding.

Communication and collaboration: Fig 3 (B) shows a stronger positive correlation between the RCI Score and Communication and Collaboration. This means that digital collaboration skills (email etiquette, sharing, participation in online groups) may be more intuitive or practiced consistently, and therefore more stable across all self-assessments. This allows us to build on this stable foundation when designing collaborative digital training.

Digital content creation: Fig 3 (C) shows a slight positive correlation, with greater dispersion of the RCI Score vs. Digital Content Creation. While some very consistent respondents scored well, others did not: content creation may be more subjective or misunderstood (e.g., adapting images). This indicates that practical tasks should be considered to validate these skills rather than relying solely on self-reporting.

Safety: Fig 3 (D) shows a slight correlation with a wider dispersion of RCI vs. Safety Score. This indicates that cybersecurity practices vary widely in perception, even consistent users may misjudge the depth of their knowledge. For this, scenario-based tests can be used for real-life cybersecurity actions (e.g., phishing identification).

Problem solving: Fig 3 (E) shows the strongest positive trend of RCI vs. Problem Solving. Consistency in responses is largely associated with better problem-solving skills, supporting the idea that reflective and strategic thinkers tend to be methodical in all domains. This implies that these students could benefit from advanced digital autonomy tools (such as automation and data modelling). So far, we have calculated the average scores per competence domain for each respondent, the overall average score (across the five domains), and added each student's RCI to contextualize.

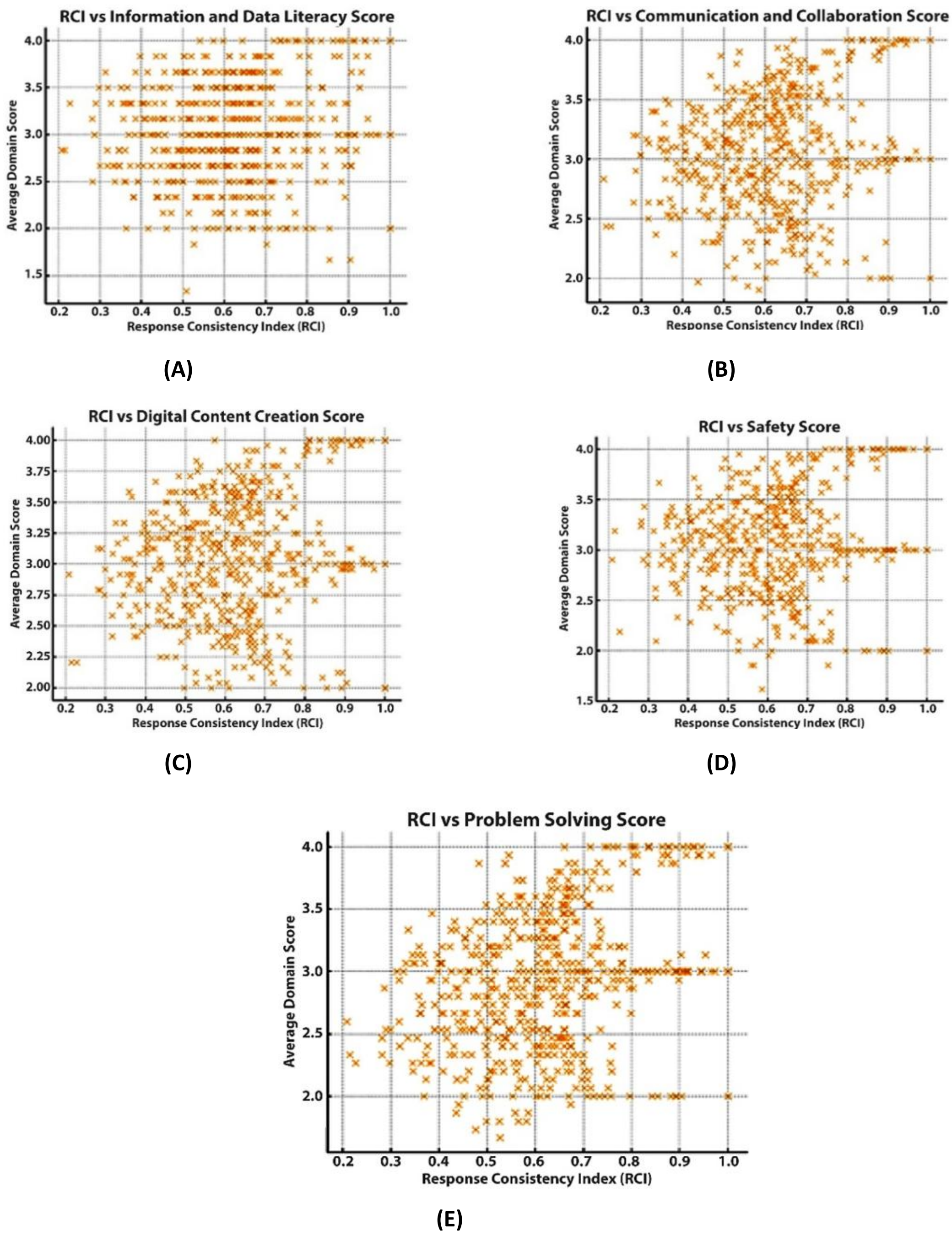

Figure 3: Scatter plots: RCI vs. DigComp 2.2. domain scores

3.3 Detailed Information by Group

Based on the results obtained, students were grouped into three performance levels: low, moderate, and high. For each group, the digital competence domain with the lowest score was identified in order to establish specific areas for improvement. The following table summarises these weaknesses, incorporating the average score obtained, as well as a pedagogical interpretation that also considers the RCI.

Below is a summary of the specific weaknesses identified by performance group, highlighting the weakest domain, its average score, and an interpretation aimed at guiding pedagogical decision-making (see Table 1).

Table 1: Specific weaknesses by performance group and consistency analysis

Weaknesses Breakdown Performance group	Weaker domain	Average score	Interpretation
Poor performance	Problem Solving	2.16	Lack of ability to identify or solve digital tasks using appropriate tools. They are probably unsure about how to customise digital tools (e.g., project management or collaboration platforms) or solve technical problems. In addition, they show moderate consistency (RCI = 0.67), which reinforces the need for intensive pedagogical support.
Moderate performance	Problem Solving	2.88	Although slightly better, it remains a significant weakness. It indicates the need for digital applications in scenarios. Its RCI (0.61) reveals a slight inconsistency, possibly related to unstable self-perception or lack of sustained commitment.
High performance	Information and data literacy	3.71	Even the best performers have relatively lower scores here, possibly struggling with source verification or advanced search techniques. Although their relative weakness lies in information literacy, they excel in digital security and collaboration (areas with higher scores).

The results allow us to draw up specific recommendations for each performance level, based on the weaknesses detected: it is evident that all groups need support in the development of problem-solving skills, although this support must be adjusted to the specific level of competence and consistency that each group presents.

Even high-achieving students need advanced training in information and data literacy, particularly in source verification, critical analysis of digital content, and identification of misinformation.

3.4 Detection of the Confidence-versus-Competence Paradox

This analysis identifies students whose self-assessment consistency (confidence) does not align with their actual digital competence (performance scores). To do this end, real-world digital tasks were used to contrast with self-perception. Two atypical profiles were identified, as described below:

3.4.1 Overly confident participants

Those who obtained an RCI ≥ 0.90, i.e., high consistency (strong self-confidence). However, their performance score is not high (low or moderate actual scores). For instance, some students identified got RCI = 1.0 because they always responded identically ("Always"). But their overall score was 2.0, which places them as low-performing students. This possible overestimation of their abilities may be due to misunderstanding of the scale, intention to appear competent, or ignorance of actual standards.

3.4.2 Uncertain participants

Those who obtained an RCI < 0.60, indicating an inconsistent self-assessment. Despite their low consistency, they showed high actual performance (true digital competence), with overall scores between 3.65 and 3.72, while their RCI was reported between 0.52 and 0.57, indicating that responses varied widely within the domains. These students may doubt their abilities or reflect more critically. Inconsistent responses, despite high performance, may reflect epistemic humility or self-aware recognition of areas for growth.

3.5 Modelling the Digital Readiness Index (DRI)

A DRI was constructed, a comprehensive and normalized score (0 to 1) that reflects the following from respondents:

- Competence in five digital domains, and

- Response consistency (RCI) as a measure of confidence or reliability.

Table 2 shows the weighting logic with the assigned factor loadings, composite reliability (CR), and average variance extracted (AVE).

Table 2: Weighting of domains for calculating the Digital Readiness Index (DRI)

Latent variable (Domain)	Indicator	Std. Factor Loading (λ)	CR	AVE
Information and Data Literacy	Item 1.1	0.82	**0.89**	**0.68**
	Item 1.2	0.79		
	Item 1.3	0.85		
	Item 1.4	0.81		
Communication and Collaboration	Item 2.1	0.85	**0.91**	**0.72**
	Item 2.2	0.88		
	Item 2.3	0.83		
	Item 2.4	0.84		
Digital Content Creation	Item 3.1	0.76	**0.86**	**0.61**
	Item 3.2	0.79		
	Item 3.3	0.81		
	Item 3.4	0.75		
Safety	Item 4.1	0.81	**0.87**	**0.63**
	Item 4.2	0.78		
	Item 4.3	0.82		
	Item 4.4	0.77		
Problem Solving	Item 5.1	0.90	**0.92**	**0.79**
	Item 5.2	0.93		
	Item 5.3	0.91		
	Item 5.4	0.89		

As shown in Table 2, the highest standardised factor loadings were observed in the Problem Solving domain (λ = 0.89–0.93), reflecting its strong contribution to the overall Digital Readiness construct. The RCI was integrated as a weighting mechanism to ensure that the DRI captures not only declared competence but also internal consistency and metacognitive self-awareness. The second-order SEM model confirmed that all five domains contribute meaningfully to the global Digital Readiness Index.

Based on this index, the top 10% of students were examined according to the Digital Readiness Index (DRI ≥ 0.90), and their characteristics and average scores were extracted to determine the behavioural patterns of top performers. Table 3 summarises the profile of this top-performing group, reporting their average domain scores, overall score, RCI, and DRI.

Table 3: Profile of the top 10% according to the Digital Readiness Index (DRI ≥ 0.90)

Summary metric of the profile of the best results	Top 10% average	Interpretation
Information and Data Literacy	3.86	Almost always check the sources and keywords.
Communication and Collaboration	3.98	Skilled communicators and digital collaborators.
Digital Content Creation	3.99	Expert in adaptation, design, and editing of digital media.
Safety	3.98	Strong awareness of cybersecurity and privacy.

Problem Solving	3.97	High capacity to customize tools to solve digital problems.
Overall score	3.95	Steady progress in all areas.
RCI (Response Consistency Index)	0.93	Highly consistent, thoughtful, and confident.
Digital Readiness Index	0.97	Practically perfect: model digital citizens.

The characterisation of the top 10% based on the DRI reveals a group of students who are not only technically competent, but also consistent and reflective in their self-assessments. These model digital citizens are a key reference point for institutional initiatives, such as mentoring programmes, peer training, or leadership in digital environments. Identifying them allows us not only to recognise high performance, but also to leverage their potential as multipliers of good practices in digital skills.

4. Discussion

Although there is general agreement on the importance of digital skills, e.g. from the early years of education (Albán Bedoya and Ocaña-Garzón, 2022; Ocaña, Almeida and Albán, 2022; Quinga et al., 2022), for teaching and learning (Bazurto Palma and Ocaña-Garzón, 2023; Ocaña et al., 2023) or professional development, doubts remain about the accuracy of DigComp 2.2.

In light of this, and in response to the research questions posed in Section 1.1, the objective of this study was twofold: first, to validate a method for assessing self-perception of digital competences (RQ1) and, second, to diagnose actual competence gaps in military university students (RQ2). The integration of these findings into the DRI construct (RQ3) addresses the overarching aim of this research. Findings confirm that simple self-perception is an insufficient and often misleading indicator of digital competence.

Our main contribution is the validation of the Response Consistency Index (RCI) as a proxy for metacognitive self-awareness and its integration into a Digital Readiness Index (DRI). This discussion is articulated along three axes: (1) the interpretation of the RCI as a qualifier of self-perception and its link to the Dunning-Kruger effect; (2) the analysis of critical competence gaps (Problem Solving and Information and Data Literacy); and (3) the value of the DRI as an alternative construct.

Theoretically, the study draws on two complementary frameworks. First, it is anchored in the metacognitive monitoring literature (Flavell, 1979), which posits that accurate self-assessment depends on higher-order cognitive processes that evaluate one's own performance. Second, it engages directly with the Dunning–Kruger model (Kruger and Dunning, 1999), extending its application from general cognitive tasks to domain-specific digital competences. The principal contribution of this study is therefore twofold: it provides an empirical operationalisation of metacognitive calibration within the DigComp 2.2 framework (via the RCI) and demonstrates that integrating calibration metrics into composite readiness indices (via the DRI) yields a more valid assessment than self-report alone.

4.1 Beyond Self-Perception: The RCI and the (In)Expert Paradox

The discrepancy between self-perceived and actual digital competence is a persistent and well-documented problem in the literature. Multiple studies, ranging from accounting students (McCourt Larres, Ballantine and Whittington, 2003; Ballantine, McCourt Larres and Oyelere, 2007) to older adults (Barboutidis and Stiakakis, 2023), demonstrate a systematic tendency to overestimate one's own abilities. The problem is exacerbated because self-assessment tools, often based on frameworks such as DigComp, can be vague and heavily biased by participants' personal beliefs (Siiman et al., 2016).

Our results not only confirm this discrepancy but deepen it. We identified profiles consistent with the Dunning-Kruger effect (Kruger and Dunning, 1999): a low-performing group with high consistency (overconfidence) and a high-performing group with low consistency (underconfidence). This duality aligns with previous research that, while confirming general overestimation, also points out that students with higher abilities tend to be more accurate in their self-assessments (McCourt Larres, Ballantine and Whittington, 2003).

Here, we interpret the RCI values as an indicator of metacognitive realism. The finding that 9.7% of the sample achieved a perfect RCI (1.0) is particularly revealing. Far from representing mastery, this group contained individuals who answered "Always" to everything, masking actual low competence. This suggests that "perfect consistency" in self-assessment may, paradoxically, be a warning sign of a lack of critical reflection.

In contrast, the RCI's weaker correlation with domains such as Safety and Digital Content Creation is equally significant. We argue that this is not a failure of the index, but rather an accurate capture of reality. A student may believe their security practices are adequate (e.g. password creation) without being aware of more complex threats. As Barboutidis and Stiakakis (2023) point out, discrepancies between self-assessment and objective assessments often emerge in specific DigComp domains.

These findings directly address RQ1, confirming that the RCI effectively captures metacognitive calibration and reveals systematic patterns of over- and underconfidence consistent with the Dunning–Kruger effect.

4.2 Critical Gaps: Problem-Solving and Information and Data Literacy

Diagnosing weaknesses by domain offers the most direct pedagogical implications. The fact that Problem Solving is the weakest domain for the low- and moderate-performing groups is a troubling finding. This competence represents the ability to apply digital knowledge strategically, and its absence indicates that students lack the ability to transfer skills to solve real-world problems.

However, the most critical finding is the relative weakness in Information and Data Literacy (RCI=0.69) even in the high-performing group. Our top-performing students, although technically competent, still show difficulty assessing credibility and verifying sources.

This finding is not isolated; recent studies in different disciplines, such as nursing (Martzoukou et al., 2024) and teacher training (Alonso García et al., 2024), also report insufficient levels of competence in information and data literacy. This refutes the myth of the "digital native" and aligns with research showing that technological fluency does not equate to critical literacy (cf. Hargittai, 2010). Indeed, mere frequency of internet use does not guarantee proficiency; research based on performance tests suggests that extensive use may lead to incorrect usage patterns and is inversely related to digital competence (Barboutidis and Stiakakis, 2023).

In response to RQ2, these results identify Problem Solving and Information and Data Literacy as the competence domains with the most pronounced discrepancies between self-assessed and actual competence, a pattern that persists even among top-performing students.

4.3 The DRI as an Alternative Model of "Digital Readiness"

Existing digital competence indices often rely solely on summing self-perception scores. The DRI proposes a methodological advance by integrating competence (DigComp) and self-awareness (RCI) into a single construct validated using CFA/SEM.

The DRI conceptualizes "digital readiness" not only as the sum of skills, but as the intersection of competence and accurate self-awareness of that competence.

The profile of the top 10% students validated by the DRI corroborates this model. These "model digital citizens" are not only exceptional in their skills (average 3.95), but also exceptionally realistic in their self-assessment (RCI 0.93). They do not suffer from overconfidence, a finding that contrasts with the widespread overestimation reported in the literature (e.g., Ballantine, McCourt Larres and Oyelere, 2007) and reinforces the idea that genuine digital mastery is, in essence, a metacognitive exercise.

More broadly, identifying training needs based solely on self-assessments can be misleading. Self-perception data may not reflect a real training need (Liesa-Orus, Blasco and Arce-Romeral, 2023), which can lead to poor decision-making, a limited understanding of actual competences, risks in research and evaluation, or difficulties in application design (Montenegro-Rueda and Fernández-Batanero, 2024; Palacios-Rodríguez et al., 2023; Silva, Usart and Lázaro-Cantabrana, 2019).

Collectively, these findings address RQ3, demonstrating that the DRI—by integrating competence, consistency, and metacognitive accuracy—constitutes a more valid and informative measure of digital readiness than self-perception scores alone.

5. Conclusions

This study empirically demonstrates that, in the era of digital literacy, how a student perceives their skills is as important as what skills they believe they possess. Blind reliance on mere self-assessment is, at best, incomplete and, at worst, misleading, as it creates an "illusion of competence" that masks the most critical skill gaps.

The fundational contribution of this research is the provision of a validated method for decoupling confidence from competence. The RCI is not a simple quality control measure; it stands as a robust proxy for an individual's metacognitive calibration. Applying this lens, our findings expose an educational paradox: students' apparent digital fluency coexists with profound strategic deficiencies, notably in Problem Solving and, critically, in Information and Data Literacy, even among the highest-achieving cohorts.

The DRI is, therefore, not just another index, but an integrated construct that conceptually redefines "digital readiness." We propose that genuine readiness lies not in the sum of technical skills, but in the integration of competence and accurate self-awareness of that competence.

Despite the robustness of the model, we acknowledge several limitations. First, the sample was drawn from higher-education military institutions, which may limit generalisability. Second, although the RCI and DI assess self-perception, the study still relies on self-report, a method whose reliability has been questioned.

Regarding the generalisability of these findings, it should be noted that the proposed methodology—particularly the RCI and DRI constructs—is not inherently limited to military populations. While the current sample was drawn from a specific institutional context, the underlying analytical framework is transferable to other higher education settings, professional training programmes, and diverse demographic groups. Future research should validate these constructs across diverse cultural, linguistic, and disciplinary contexts to test their broader applicability. Cross-national studies using the DigComp 2.2 framework would be particularly valuable in this regard.

A future line of research is the triangulation of these findings with performance-based tasks, an approach already used successfully to identify usage patterns and compare self-reported performance with objective performance. Furthermore, the DRI and the RCI should not only as diagnostic tools, but also as tool for pedagogical intervention. Future studies should explore whether pedagogical interventions focused on metacognition can improve RCI and whether this improvement leads to an improvement in actual digital competence.

For educational policy and curriculum design, the message is unequivocal: it is no longer enough to teach digital tools; it is imperative to teach students to think critically about how they use those tools. The future of digital literacy lies not only in closing the skills gap, but in closing the much more dangerous gap of self-awareness.

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