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Digital Competence Requirements for Students of IT and Computer Science: the University Faculty Perspective

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Digital Competence Requirements for Students of IT and Computer Science: the University Faculty Perspective

Abstract. Digital technologies now permeate all spheres of life, making digital competence a key prerequisite for learning, work, and civic participation. Demands for digital competence differ in secondary, further, and higher education. They are particularly high in Information Technology and Computer Science (IT&CS) programmes, where students are expected not only to use but also to design and innovate with digital technologies.

This study identifies and structures university faculty expectations regarding the initial digital competences of first year IT&CS students at Faculty of Mathematics and Informatics at Sofia University, Bulgaria.

Faculty participated in a Group Concept Mapping, a participatory mixed-methods and consensus-driven research approach, integrating structured brainstorming, sorting, rating, and multivariate analysis (multidimensional scaling and hierarchical cluster analysis) to produce a conceptual model of expected digital competence.

The analysis yielded five-cluster model spanning domain-specific competences (*basic programming skills*; *basic operations with data, software, and hardware*) and generic competences (*digital literacy*; *effective communication and ethical behaviour*; *information literacy and critical thinking*). Importance and feasibility ratings revealed distinctive priority patterns: generic competences were rated as highly important and relatively feasible, whereas several domain-specific expectations were seen as important but less feasible at the entry level. These patterns highlight tensions between what faculty consider essential and what they believe current school preparation provides. The study's contributions are: (i) a faculty derived, empirically structured model of expected digital competence for incoming IT/CS students, (ii) evidence of priority patterns and tensions between importance and feasibility across competence clusters, and (iii) actionable implications for the school-university transition and curriculum alignment, including targeted strengthening of high priority generic competences (21st century skills), clearer articulation of entry level programming and data expectations, and the use of the cluster structure as a shared planning tool for stakeholders.

Keywords: Digital Competence, Domain-Specific and Generic Expectations Regarding Digital Competences, Group Concept Mapping.

1 Introduction

Digital technologies now permeate learning, work, and civic participation, making digital competence a crucial prerequisite for an active and fulfilling life. International frameworks such as DigComp 2.2. (Vuorikari et al., 2022), Computing Curricula 2020 (IEEE-CS & ACM, 2020), and ISTE Standards (ISTE, 2016) converge in portraying

digital competence as multidimensional, integrating technical skills with information literacy, communication, collaboration, ethical awareness, and 21st-century skills like critical thinking and self-directed learning.

Despite a growing body of research on digital competences across different contexts (Bogdány et al., 2024; Mejías-Acosta et al., 2024; Tzafilkou et al., 2022), studies specifically addressing digital skills in higher computer science education remain scarce (Groeneveld et al., 2020; Weiser et al. 2022;).

Digital competence development is now embedded in school curricula in many countries, guided by frameworks such as DigComp 2.2, progressively integrated from early schooling through upper secondary education (European Commission/EACEA/Eurydice, 2019; OECD, 2023). Policy documents emphasise continuous, cumulative development, with secondary education building on primary and higher education building on secondary outcomes. However, Information Technology and Computer Science (IT&CS) programmes require more complex, specialised profiles than general pathways. In the context of computer science education, digital competence combines advanced domain-specific skills (programming, data operations, system thinking) with the ability to critically, ethically and effectively use and develop digital technologies (Kumar, et al., 2024; National University, 2025). A high initial level of digital competence of incoming university students is needed to ensure they are sufficiently equipped for intensive future-oriented programs.

Entry requirements are expressed formally through admission criteria and informally via course prerequisites, assumed knowledge, and pedagogical methods. When there is a mismatch between school outcomes and faculty expectations, students face difficulties, which impact learning paths, increase dropout drop-out risk, and eventual competence. To understand this gap, it is important to analyse not only what competencies are expected but also how expectations are organized, which areas are prioritized, and where faculty see potential feasibility constraints.

This study aims to examine faculty perspectives at a leading [blinded for review] university within a national context where digital competence has been systematically integrated across school levels, and specialized upper-secondary IT programs exist. As part of a broader three-stage research project, this work aims to identify academic staff's expectations regarding the initial digital skills of first-year IT & CS students using Group Concept Mapping, a participatory mixed-methods approach.

The study makes three key contributions to learning technology research and practice. First, it creates a faculty-driven, empirically based model of expected digital competence for incoming IT/CS students. Second, it uncovers priority patterns and tensions through importance and feasibility ratings, showing where expectations tend to cluster (e.g., generic competencies rated highly important and feasible) and where tensions appear (e.g., domain-specific skills considered important but less feasible at entry). Third, it offers concrete, actionable recommendations for the school–university transition and curriculum alignment, identifying which competence groups need strengthening at the upper-secondary level and how higher education programs can better support entry-level digital skills. These contributions directly benefit learning technology stakeholders involved in designing, aligning, and supporting digitally intensive pathways in IT & CS education.

2 Methodology

Within curriculum design research, which has shifted from a top-down to a more collaborative process, Group Concept Mapping (GCM) is increasingly positioned as an alternative to more traditional data-gathering and synthesis methods such as interviews, surveys, affinity diagram and Q-sorting. Group Concept Mapping (GCM) is systematic, multi-step, participative, consensus-based, mixed-method research approach (Kane & Trochim, 2007; Kane & Rosas, 2017). As a participative method, GCM focuses on researching with people, not on people. The method combines the strengths of participants' expertise with their contextual insight and ownership, prioritizing the voices of those most closely associated with or affected by the problem under investigation. As a mixed research method, GCM integrates nominal group process in qualitative data collection—such as generating, classifying, and prioritizing ideas—with quantitative analysis methods such as multidimensional scaling and hierarchical cluster analysis. Participants independently brainstorm, sort, and rate statements. Their sorting data are then aggregated and analysed using multidimensional scaling (MDS) and hierarchical cluster analysis (HCA). This approach was appropriate for examining faculty expectations that are partly tacit, multidimensional, and not adequately represented by a predefined competency list.

2.1 Procedure and key decisions

The GCM process comprises several stages: preparation, idea generation, idea synthesis, structuring (sorting and rating), quality review, analysis, and interpretation (**Fig. 1**).

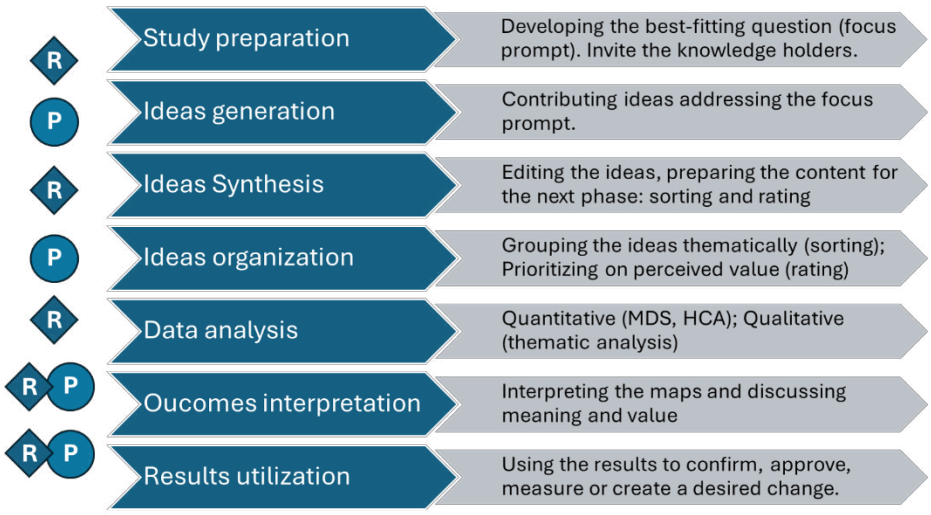

Fig. 1 The basic GCM Process (P = participant; R = researcher. Source © 2016/2017 Concept System Inc. (adapted)

During the presented study GroupWisdom™ online environment (`https://GroupWisdom.tech/`) supported the whole process of data collection and analysis, providing data visualization for the interpretation stage.

Preparation

The research team defined the focus for idea generation and rating, identified participants, and prepared the online environment for data collection and analysis. The focus prompt is formulated in complete-sentence format to elicit concise, domain-specific statements (e.g., "One specific expectation of the basic digital competence of students entering their first year is…"). Rating criteria (e.g., importance and feasibility) were operationalized using Likert scales (e.g., "Rate each expectation on a five-point scale where '1' means 'Not at all important', '5' means Very important'; and "Rate each expectation on a five-point scale where '1' means Not feasible at all, '5' means' Very feasible.').

Idea Generation and Synthesis

Participants generated 89 raw statements in response to the focus prompt via the online platform (GroupWisdom™, 2002). These statements were then synthesized into a refined set of unique, clear, and relevant items. The purpose of this stage was to obtain a list of unique ideas, with only one idea per statement; ensure that each idea is relevant to the focus prompt; ensure that the ideas are clear, understandable, and rateable; and reduce the number of ideas so that it is manageable for sorting and rating. It was not recommended to prioritize, select based on perceived value, or delete unpopular ideas. The process involved identifying keywords, assigning a code word to each keyword's configuration, grouping similar ideas, and reducing redundancy while preserving the breadth of perspectives. As a result, 67 clear, unique, and rateable statements remained.

Organizing: Sorting and Rating

Participants independently grouped statements into thematically meaningful clusters without predefined constraints and assigned labels to each group. They subsequently rated each statement on predefined criteria (e.g., importance, feasibility), using the full-scale range and relative comparison across items. The task was performed in the GroupWisdom™ platform.

Quality Review

Data were screened by researchers to ensure adherence to sorting and rating guidelines (e.g., avoiding overly few or excessive groupings, inappropriate labels, or uniform ratings). There were no violations of the rules for sorting and rating.

Data Analysis

GCM data analysis has a strong mathematical grounding. Non-metric multidimensional scaling (MDS) and Hierarchical Cluster Analysis (HCA) were applied to transform qualitative inputs into quantitative representations (Galbraith et al., 2002; Kruskal & Wish, 1978). Individual sorting data were converted into binary similarity matrices,

which were aggregated into a total similarity matrix. MDS then generated a two-dimensional point map, where spatial proximity reflected the frequency with which items were grouped together. Two key indicators supported interpretation: **stress value** and **bridging value**. Stress value (goodness-of-fit) assessed how well the point map represented participants' raw sorting patterns. The bridging value ranges from 0 to 1 and indicates the frequency with which a statement has been grouped with others. A lower bridging value indicates that a statement was sorted with nearby statements on the map, while a higher bridging value suggests that it was sorted with statements that were further apart. In GCM, the strength of association of an idea with any other idea on the map can be visualized through a spanning analysis, which was used at the beginning to identify areas on the point map that were more or less populated with ideas.

HCA (using Ward's algorithm) groups items into clusters based on their spatial proximity. The number of clusters is determined iteratively supported by spanning analyses and interpretive judgment.

Outcomes' interpretation: Cluster selection and labelling

To determine the best-fitting number of clusters for the purpose of the study, three researchers used the practical heuristics method known as '15-to-5' (Kane and Trochim, 2007) which has also been supported by research (Rosas and Kane, 2012). They began by creating a 15-cluster solution and then evaluated the relevance of the hierarchical clustering algorithm's recommendations for merging clusters at each subsequent step, examining content coherence and granularity. The decision on the cluster names was made after reviewing the clusters' content and the software's suggestions.

Cluster-level importance and feasibility ratings were compared using pattern-match diagrams (ladder graphs), which visualise the relationship between the two dimensions.

All the calculations and visualizations were generated by the GroupWisdom™ software, while the interpretation was presented by the researchers. The stage of final decisions also involved the participants.

Utilization

Following the analysis, researchers and participating faculty jointly reviewed maps, clusters, and ratings to interpret their substantive meaning and implications for curriculum alignment.

2.2 Sampling and participants

The study was conducted in the Sofia University's Faculty of Mathematics and Informatics, which has a strong impact on national education policies.

An invitation letter was sent to 22 professors teaching first-year Computer Science and IT students; 16 volunteered and provided informed consent. All participated in brainstorming, sorting, and rating activities; 11 completed all tasks.

Participants were predominantly experienced (>10 years of university teaching), with a slight female majority (**Fig. 2Error! Reference source not found.**).

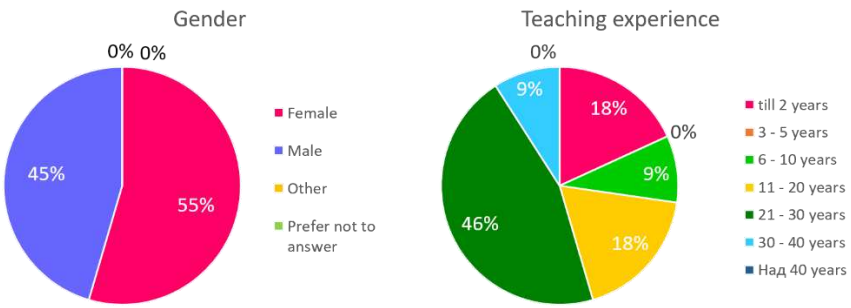

Fig. 2 Participants' background characteristics

They taught 20 disciplines, mostly in Computer Science and IT (**Fig. 3**). The sample represents diverse subject expertise across the IT&CS curriculum, supporting breadth of perspectives on entry-level digital competence requirements.

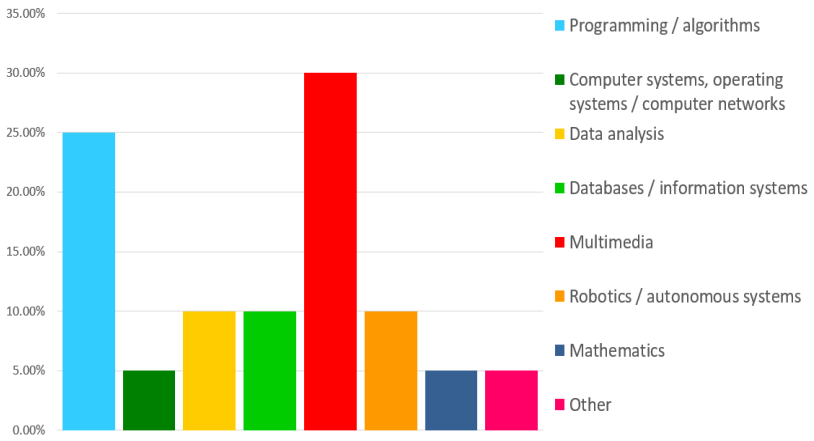

Fig. 3. Academic disciplines taught by the participants (Note: Some participants teach more than one discipline)

3 Results

3.1 Digital competence expectations (Point Map and Cluster Solution)

Based on MDS analysis of 67 ideas about the expected level of digital competence of incoming students collected in the study, a point map of the collected statements (**Fig. 4**) was generated, where statements that are closer on the map can be expected to be close in meaning.

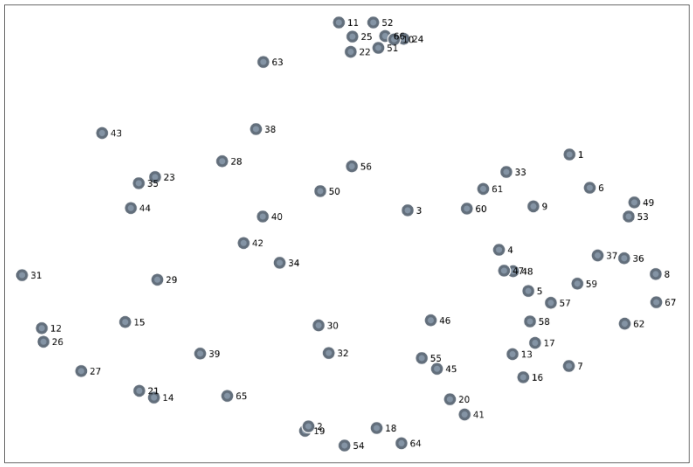

Fig. 4. Point map of the collected statements on expected digital competence of the incoming students (*Note: GroupWisdom™ randomly assigned unique identifiers to each statement. In the figure dots represent statements with their unique identifiers*)

HCA generated candidate solutions. Following the 15-to-5 heuristic and iterative content review, a five-cluster solution was selected as the most interpretable and best fitting the data. The clusters represent distinct yet related digital competence domains:

1. Basic programming skills (8 statements, avg *bv*=0.05)
2. Basic operations with data, software, and hardware (24 statements, avg *bv*=0.36)
3. Digital literacy (12 statements, avg *bv*=0.41)
4. Effective communication and ethical behaviour (10 statements, avg *bv*=0.53)
5. Information literacy and critical thinking (13 statements, avg *bv*=0.49)

Labelling the clusters was a challenging task because all of them combine the 21st century skills with various digital competences. While all clusters except cluster 3 *Digital literacy* have clearly defined characteristics reflected in their names, the reffered cluster includes sentences that correspond to the basic “ability to understand and use information in multiple formats from a wide range of sources when it is presented via computers” (Gilster, 1997), which is considered the first official definition of the term "Digital literacy" (Secker, 2017).

Fig. 5 visualizes the cluster map. **Table 1** provides cluster descriptions and two illustrative statements per cluster.

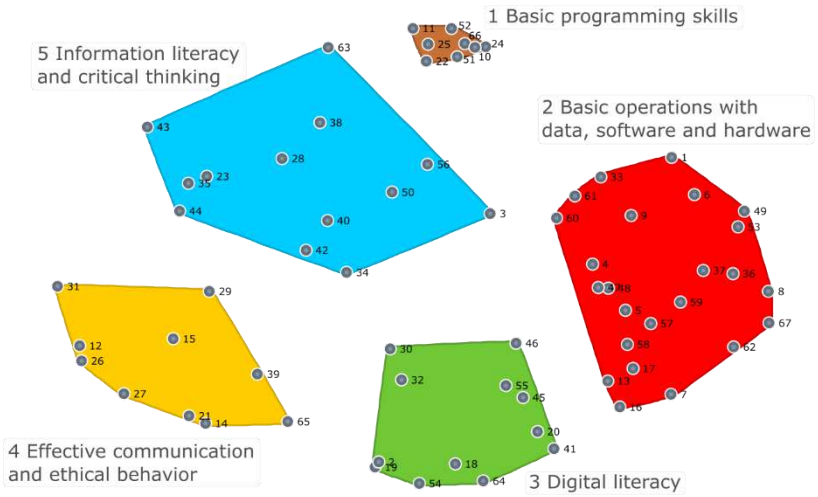

Fig. 5. The cluster map representing 5 thematic clusters with their constituent ideas

Table 1. Thematic clusters and constituent exemplary statements with bridging values

Clusters (*n* statements, average *bv*)	**Statements in the cluster represent expectations of the faculty on:**	**Examples of statements with their unique identifiers and their bridging values**
1. Basic programming skills (8 statements, bv=0.05)	Expectations of the faculty on what the entrance students should be able to do as in programming and coding	52. Understanding of basic programming concepts and proficiency in one or more programming languages (e.g. Python, JavaScript) is welcome (0.00) 51. Can solve simple problems using basic algorithms and logical reasoning (0.06)
2. Basic operations with data, software, and hardware (24 statements, bv=0.35)	The ability to use different devices, and to operate with software, perform data analysis, including statistical calculations, and creating visual representations of data. Skills of ensuring basic security of the systems and data.	67. Can install and configure basic operating system settings (0.29) 61. Can use spreadsheet software (e.g. Excel, Google Sheets) to analyse data, perform statistical calculations, and create visual representations of data (0.36)

3.	Digital literacy (12 statements, bv=0.41)	Basic digital skills, such as the using e-mail, designing visual presentations and usage of a shared environment for collaborative work. Keeping personal physical and mental health, and privacy and reputation	55. Can use email, instant messaging and other communication tools (0.35) 64. Know how to protect their accounts and devices from malware and attacks. (0.41)
4.	Effective communication and ethical behaviou (10 statements, bv=0.53)r	Knowledge of how to communicate with different target groups, "soft" communication skills, and ethical behaviour in the digital space.	27. Demonstrate ethical behaviour online (0.35) 14. Are proficient in a digital communication style appropriate to the profile of the intended interlocutor (0.49)
5.	Information literacy and critical thinking (13 statements, bv=0.49)	Knowledge and skills of working with information – searching, analysis, selection and critical evaluation of information.	63. Can formulate problems and create coherent solutions by breaking tasks down into smaller steps (0.32) 42. Can search for relevant sources on a topic, rather than using the first one encountered after literally typing the question (0.47)

3.2 Cluster coherence

Bridging values indicate cluster coherence. As can be seen in **Table 1**, cluster 1 (*Basic programming skills*) has the lowest *bv* (0.05), indicating strong participant agreement on constituent statements. Cluster 2 (*Basic operations*) is also relatively coherent (*bv*=0.35) despite containing many statements over the expected domain-specific knowledge and skills. Clusters 3, 4, and 5 show higher *bv* (~0.4–0.5), indicating less coherence and greater participant disagreement on the statement groupings.

Two of these less coherent clusters contain statements that have high or maximal *bv* of 1. These are statements 21 (*Know and follow basic rules for ergonomic work with a computer*, *bv*=0.7) and 31 (*Can work in a team*, *bv*= 0.7) in the thematic cluster 4. *Effective communication and ethical behaviour*, and statement 43 (*Experience with self-directed learning approaches is welcome*, bv = 1) in the thematic cluster 5. *Information literacy and critical thinking*.

3.3 Strengths of Connections Between Statements (Spanning Analysis)

The illustrative examples of spanning analysis (Fig. 6 and Fig. 7) were used to explore how high-bridging statements connect across clusters.
Statement 31 (*Can work in a team*) is connected with statements in all clusters except Cluster 1, with the strongest connection to statement 65 (*Can work effectively in teams using online collaboration platforms such as Google Docs or Microsoft Teams*). As a core 21st century – collaboration (Voogt & Knezek, 2021), teamwork bridges generic clusters and domain specific clusters involving collaborative use of digital tools (Fig. 6).

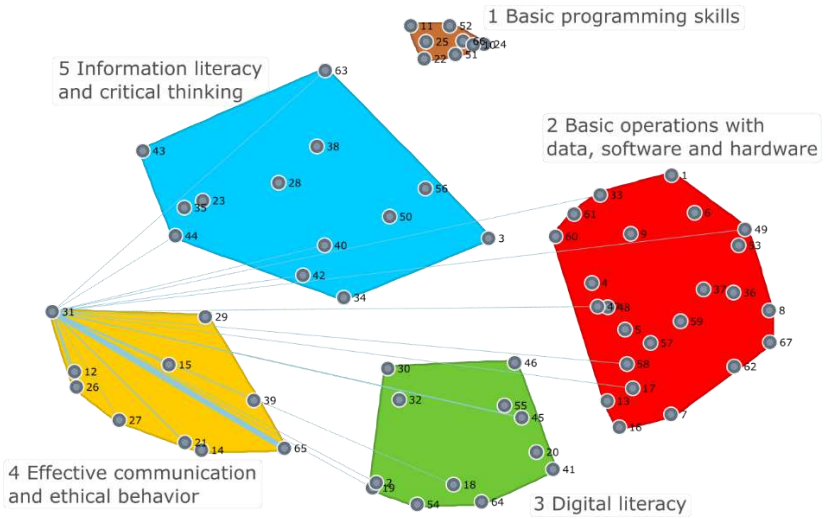

Fig. 6. Spanning analysis of statement 31 (*Can work in a team*)

Statement 43 (*Experience with self-directed learning approaches is welcome*) had the highest bridging value (1.0). Its spanning diagram (Fig. 7) shows a strong link to Cluster 2, including statements about using specific software, interactive learning resources, and learning management systems. This suggests faculty view self-directed learning as closely tied to students' ability to independently acquire new domain-related skills and use digital technologies as learning tools. Together, these examples indicate that 21st-century competences such as collaboration and self-regulated learning are treated as integral elements of digital competence rather than separate generic attributes.

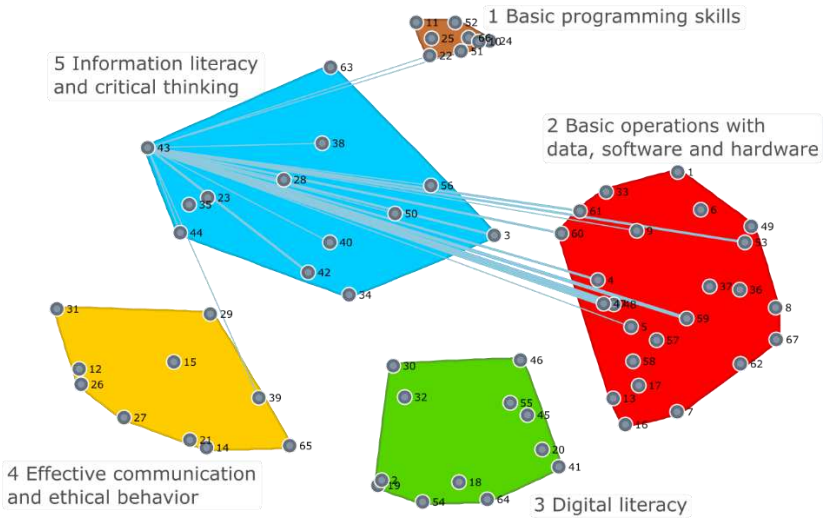

Fig. 7. Spanning analysis of statement 43 (*Experience with self-directed learning approaches is welcome*)

3.4 Importance and Feasibility of Digital Competence Expectations

Cluster-level averages for importance and feasibility revealed distinct priority patterns (**Error! Reference source not found.**, Fig. 8). Overall, a strong association between the dimensions ($r = 0.91$) was observed, yet notable differences emerged.

Table 2. Clusters' importance and feasibility means

Cluster	Importance (M)	Feasibility (M)
1. Basic programming skills	3.43	3.14
2. Basic operations with data, software and hardware	3.77	3.70
3. Digital literacy	4.38	4.18
4 Effective communication and ethical behavior	4.12	3.91
5. Information literacy and critical thinking	4.14	3.64

Cluster 5. (*Information literacy and critical thinking*) scored significantly higher on importance than on feasibility (M Importance = 4.14, SD = 0.42; M Feasibility = 3.64, SD = 0.25). The Welch's t-test for unequal variance indicates that this difference is

significant: $t(24) = 3.07$, $p = 0.0011$. This is the only significant within-cluster difference, suggesting participants are more sceptical about incoming students possessing these important skills at entry.

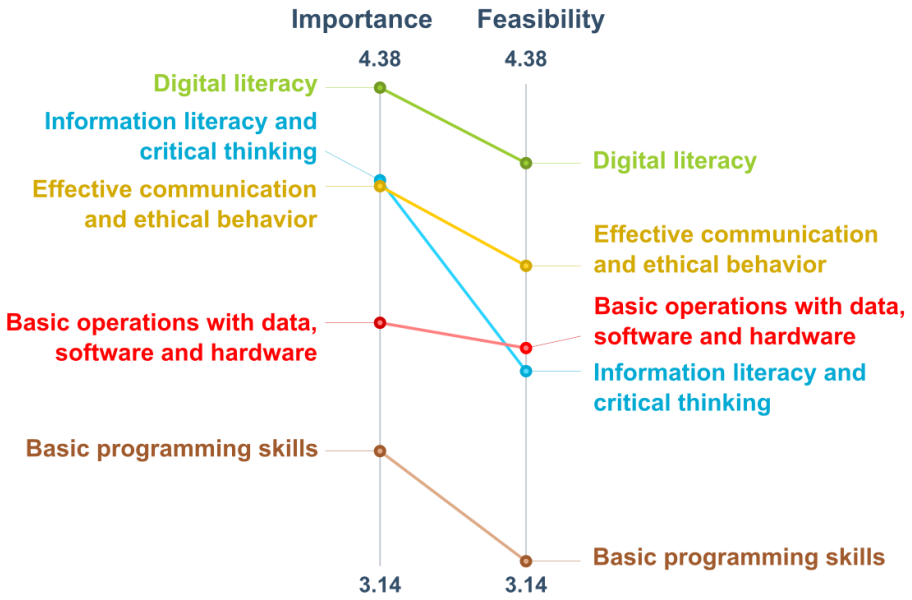

Fig. 8. Comparing the clusters on importance and feasibility

Comparison of cluster-average values along the same dimension indicates greater differences in how university teachers evaluate the importance and feasibility of more generic digital competences versus more profession-related basic skills.

Thus, the average rating of the cluster *Digital literacy* (M = 4.38, SD = 0.21) is significantly higher on the importance dimension than the rating of clusters *Basic programming skills* (M = 3.43, SD = 0.39) and *Basic operations with data, software and hardware* (M = 3.77, SD = 0.45), respectively, $t(18)=6.26$ $p=0.0000$ and $t(34)=5.65$, $p=0.0000$. *Digital literacy* is also considered more feasible to attain than *Basic programming skills* or *Basic operations skills,* and *Information literacy*. The difference is statistically significant.

These outcomes suggest that the faculty consider **generic digital skills as more important and feasible than domain-specific skills** at the entry level. Feasibility expectations might imply that the university teachers have a greater faith in the level of generic competences attained at school than in the domain-specific skills and competences.

The faculty expressed confidence in their ability to develop programming skills if students possess solid digital literacy: "If students have well-grounded basic digital literacy, I can develop their programming skills in a short time." They also noted diversity in student backgrounds—some from specialized IT schools with advanced preparation, others from general schools—requiring courses to start at lower levels.

When rating the feasibility, academic teachers rely on their intuitive expectations of school graduates' maturity, without being familiar with the expected outcomes outlined in the state's standards for general schooling. When discussing the competence level of students from specialized schools, some university teachers say they cannot fully trust them. Professors indicate that it takes them more time to untrain students from some ineffective practices than it does to build useful habits. This experience might explain the lower rate of the feasibility of both clusters – *Programming skills* and *Operations with data, software and hardware*.

The data can be obtained from: https://osf.io/97yuj/overview?view_only=efe7f50554c64cae9106a7d978ff700b

4 Discussion

4.1 Key findings

This study identified faculty expectations for incoming IT&CS students' digital competences, resulting in five thematic clusters: two domain-specific (*Basic programming skills*; *Basic operations with data, software, and hardware*), and three generics (*Digital literacy*; *Effective communication and ethical behaviour; Information literacy and critical thinking*). These findings align with research in Computer Science education (Groeneveld et al., 2020; Weiser et al., 2022; Yechkalo, et al., 2025) and broader frameworks emphasizing multidimensional digital competence integrating technical, cognitive, social, and ethical dimensions.

A key finding is that faculty rated **generic competences significantly higher than domain-specific skills** in both importance and feasibility. This pattern aligns with van Laar et al.'s (2017) framework which identifies core 21st-century digital skills (such as information management, communication, collaboration, critical thinking, and problem-solving) and contextual skills (including ethical awareness, cultural awareness, self-direction, and lifelong learning). The three generic clusters in this study closely correspond to these dimensions, indicating a global agreement that modern digital competence goes beyond operational technical skills to include critical, ethical, and socio-communicative abilities.

Notably, high-bridging statements (*Experience with self-directed learning*, *Can work in a team*, *Ergonomic work rules*) often co-occur with domain-specific clusters, showing that faculty increasingly see 21st-century skills as part of digital competence rather than separate traits. This integration reflects the changing view that effective use and creation of technology require not only technical skills but also self-regulation, collaboration, and ethical awareness (Vuorikari et al., 2022).

Although the model was derived at one Bulgarian university, its relevance is not limited to this institutional setting. The five clusters correspond broadly to dimensions reflected in international frameworks, including technical creation and problem solving, information and data literacy, communication and collaboration, safety, and ethical use of digital technologies (Vuorikari et al., 2022; IEEE-CS & ACM, 2020; ISTE,

2016). The model should therefore be understood not as a universal list of entry requirements, but as a transferable analytic framework for eliciting and structuring locally situated expectations. Its specific content, cluster boundaries, and priority patterns may differ across higher education systems because national school curricula, admission routes, specialist IT pathways, and access to digital learning opportunities shape the competence profile with which students enter university. Cross-institutional applications could compare both the stability of the five broad domains and variations in their importance and feasibility ratings, thereby linking international frameworks to the realities of particular education systems.

The gap between importance and feasibility ratings, particularly for *Information literacy and critical thinking* (Cluster 5), highlights potential misalignment between secondary school outcomes and university expectations. Faculty confidence in teaching programming contrasts with scepticism about students' preparedness in generic competences, suggesting these areas may be under-valued in current school curricula despite their recognized importance. This resonates with evidence that university entrants often exhibit higher basic digital literacy than advanced domain skills (van Laar, et al., 2017; Zhao et al., 2021), yet the present findings suggest even generic skills may not meet faculty expectations in depth and sophistication.

4.2 Limitations

The small, single-institution sample (n = 11) limits the transferability of the findings. The results should therefore be interpreted as a structured account of the participating faculty's expectations rather than as representative of all IT/CS programmes. Systematic procedures were followed for determining the ideas for sorting and rating, yet some concepts may be over- or underrepresented. The five-cluster solution balances granularity and parsimony. However, alternative partitions might yield different conceptual emphases.

The proprietary software GroupWisdom™ supported online data collection, standard GCM analyses, and visualisation. Data security is ensured through GDPR-compliant infrastructure hosted on secure cloud services. In spite of its advantages, the use of software also entails certain limitations: – proprietary algorithms, fixed parameters, vendor dependency, cost, limited long-term reproducibility transparency. To mitigate this limitation, the study makes the primary sorting and rating data and derived outputs available. The reported non-metric MDS and Ward's HCA procedures can be reproduced using open-source statistical environments, such as R or Python (Bar & Mentch, 2017), although doing so requires technical expertise.

GCM is resource-intensive and provides less contextual detail than in-depth qualitative methods (Rosas & Kane, 2012). The unconstrained sorting task may yield heterogeneous sorting logics, while researcher decisions concerning statement synthesis, selection and labelling of the cluster solution can influence interpretation (Trochim & Kane, 2005). Alternative analytical sequences, including applying HCA before MDS, have been proposed to improve cluster coherence (Péladeau et al., 2017). Critics further caution that a single aggregate map can obscure subgroup perspectives when participants apply different criteria in their sorts, and that reducing relationships to two MDS

dimensions may lose conceptual detail or generate statistically convenient rather than substantively meaningful clusters (Kampen et al., 2026). GCM can also examine subgroup perspectives through multi-map comparison techniques when sample size and study design permit (Rosas, 2017; Stoyanov et al., 2017).

GCM incorporates multiple mechanisms to enhance trustworthiness. Independent idea generation, sorting, and rating reduce social influence biases such as groupthink and researcher-led coding. The sample, although small, included experienced academic staff from diverse Computer Science and IT teaching areas, supporting the relevance of the elicited expectations. The idea synthesis stage ensures clarity and relevance of statements prior to analysis.

The stress index serves as a key indicator of model fit. The calculated MDS **stress value of 0.2926** fell within the acceptable GCM range 0.20 – 0.36 (Rosas & Kane, 2012), indicating satisfactory fit between aggregated sorting data and the MDS configuration. To facilitate scrutiny, the primary sorting and rating data, derived matrices, cluster assignments, and rating data are available in the project repository.

Welch's t-test was used to assess significance because it performs well with unequal variances and small samples, and it is more conservative in controlling Type I errors (Derrick, Toher, & White, 2016) than alternatives test.

The model reflects the expectations of academic staff in a specific IT/CS faculty and therefore combines disciplinary and institutional specificity. Faculty expectations are especially valuable for identifying tacit assumptions embedded in first-year curricula, but they do not directly measure students' actual competence, school-level provision, or labour-market needs. Their views may also be shaped by disciplinary traditions, local course design, and prior experience of heterogeneous student cohorts. Future research should therefore triangulate the model with evidence from incoming students, school teachers and curriculum documents, and employers. Student perspectives could identify perceived preparedness and transition challenges, while employer perspectives could clarify how entry-level expectations connect to longer-term professional and technological demands. Comparative studies across institutions and national systems could also test which clusters are stable and which are context dependent.

GCM is relevant for conceptualisation in curriculum design, but it does not replace pedagogical expertise when translating maps into concrete syllabi (De Ries et al., 2021). In this study, GCM outputs were treated as structured evidence for interpretation—not as definitive representations of faculty expectations—and were reviewed jointly by researchers and participating faculty in relation to the study context.

5 Conclusions

This study moves beyond a descriptive list of digital competences by providing an **empirically structured faculty-derived model** of university expectations for incoming IT&CS students. The five-cluster concept map and associated rating patterns clarify not only which competences matter most, but also where faculty perceive tensions between importance and feasibility, offering a practice-grounded lens on how digital competence requirements are prioritised in higher computing education.

The study validates the international trend toward integrating socio-emotional, critical, and ethical dimensions into digital competence definitions, moving beyond narrow technical focus. By documenting differentiated importance and feasibility perceptions, the findings provide actionable insights for curriculum designers and policymakers seeking to align secondary and university education with contemporary technological and professional demands.

5.1 Contributions to learning technology research and practice

(i) Faculty-derived, empirically structured model

Unlike frameworks developed through expert consensus or literature review, this model emerges from participatory mapping of faculty tacit knowledge, organized through multivariate analysis into a visual, relational structure. The five clusters—spanning domain-specific skills (programming; data/software/hardware operations) and generic competences (digital literacy; communication/ethics; information literacy/critical thinking), including even more advanced contemporary concepts, such as using AI ethically and for content creation and evaluation —represent how faculty conceptually organize and interrelate expectations, providing a grounded reference for curriculum designers, policymakers, and learning technology researchers.

(ii) Evidence of priority patterns and tensions

Importance and feasibility ratings revealed distinctive patterns: generic competences consistently rated higher than domain-specific skills, with *Digital literacy* significantly surpassing *Basic programming* and *Basic operations*. Yet *Information literacy and critical thinking* showed significant importance-feasibility gap, indicating faculty recognize this cluster's criticality but doubt current school preparation adequacy. High-bridging statements (*self-directed learning*, *teamwork*, *ergonomic practices*) connect across clusters, demonstrating that 21st-century skills are now viewed as intrinsic to digital competence rather than separate attributes. These patterns illuminate not just *what* faculty expect but *how much* they prioritize different areas and *where* they perceive feasibility constraints – essential intelligence for curriculum alignment efforts.

(iii) (iii) Actionable implications for school–university transition and curriculum alignment

The five-cluster framework can support implementation in three connected ways. First, during curriculum review, schools and universities can map upper-secondary learning outcomes, admission expectations, and first-year module prerequisites against the five clusters. This can identify areas in which university expectations are high, but school preparation is perceived as insufficient, particularly in information literacy and critical thinking. Second, GCM is well-known for its fit-to-scale development (Rosas & Ridings, 2017). In this respect, institutions can develop low-stakes entry diagnostics combining self-report with short scenario-based or performance tasks, such as applying basic programming logic, interpreting data in a spreadsheet, evaluating online sources, selecting secure digital practices, or collaborating through an online workspace. Rather

than producing a single overall score, these diagnostics could generate learner profiles across the five clusters and guide targeted support.

Third, the framework can support a structured school–university dialogue on how expected competences are operationalised in practice. As a planned subsequent stage of the broader research programme, we proposed to engage experienced CS/IT school teachers in Nominal Group Technique (NGT) research to map effective teaching practices to the five faculty-derived clusters and to compare teachers' importance and feasibility ratings with those of university faculty. Such work can identify practical approaches through which schools may enact curriculum intentions, particularly in high-priority or lower-feasibility areas, and can inform shared transition recommendations. The results of that subsequent work are outside the scope of the present study.

Finally, technology-enhanced transition support could provide targeted pre-entry or first-semester micro-modules, interactive practice tasks, automated feedback, peer-collaboration activities, and referral to academic support. For example, students requiring support in information literacy and critical thinking could complete short modules on search strategies, source evaluation, problem decomposition, and responsible use of generative AI before or alongside introductory IT/CS courses.

5.2 Broader significance

For learning technology audiences, this study demonstrates how participatory mixed-methods approaches can surface and structure stakeholder knowledge in under-theorized domains, producing empirically grounded models that inform curriculum design, learning analytics, and technology-enhanced learning interventions. GCM method provides a replicable logic that can be applied across different contexts.

The findings validate international trends integrating socio-emotional, critical, and ethical dimensions into digital competence definitions, documenting how these manifest in faculty expectations within a specialized IT/CS context.

This paper reports a context-dependent Group Concept Mapping (GCM) case study. Rather than aiming for statistical generalization—drawing inferences from a sample to a population—case studies typically contribute to analytical generalization, in which findings are extended to conceptual frameworks (Flyvbjerg, 2006; Yin, 2018). Consistent with the outcomes of several digital-competence frameworks (Vuorikari et al., 2022; IEEE-CS & ACM, 2020; ISTE, 2016), the GCM contributes to cumulative and comparative knowledge of digital-competence frameworks. GCM identified how and why findings occur and revealed the mechanisms underpinning their relationships, an instance of mechanism-based reasoning generalizability (Ritchie et al., 2014). The GCM method provides a replicable logic that can be applied across contexts to address the question: "Under what conditions is this likely to apply elsewhere?" Transferability of case-study findings can also be assessed through rich, thick description, which enables readers to judge fit and relevance and to determine whether findings are transferable, adaptable, or replicable in their own settings—an approach often described as naturalistic generalization (Stake, 1978). Triangulation further enhances transferability: GCM inherently integrates qualitative and quantitative data collection and analysis

methods and forms part of a mixed-methods approach. Its findings will subsequently inform broader curriculum-development activities.

In the presented context, rather than prescribing a fixed international standard, the model offers a replicable approach through which institutions can align international digital competence frameworks with local curriculum conditions, disciplinary requirements, and the support needs of incoming students.

6 Ethics

All participants enrolled voluntarily after signing an informed consent form. The study was conducted in accordance with the Declaration of Helsinki, and approved by the Ethics Committee of Sofia University St. Kliment Ohridski (protocol code No. 93-P-289/19 December 2023).

7 Availability of data

The list with all the statements, clusters, primary data, and calculations could be found at https://osf.io/97yuj/overview?view_only=efe7f50554c64cae9106a7d978ff700b

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Statements and Declarations

There are no financial or non-financial interests that are directly or indirectly related to this study.

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