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Competency Profiles In Digital Information Judgment And Use Across Countries: Digital Empowerment Or Structural Constraints?

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Abstract–*Digital capabilities are widely recognized as the key to promoting social participation, enhancing information judgment and realizing individual empowerment. However, the formation of competence is not only influenced by individual factors, but also rooted in the distribution of institutional arrangements, cultural traditions and structural resources. Based on Giddens' structuration theory and the classical information behavior model, this paper combines the research on digital empowerment pathways to construct an analytical framework of "structure-empowerment-competency portrait", from which this study explores how factors such as gender, age, and geographic location shape the individual's ability in the digital environment. In this framework, we explore how factors such as gender, age, and geography shape the performance of individuals in digital environments.*
The study utilizes data from 61 countries released by the International Telecommunication Union (ITU) and employs descriptive statistics, and regression modeling to identify the significant pathways through which structural disparities influence key dimensions of digital competence, including information judgment, content creation, and collaboration and communication. The results indicate that different social groups face unequal opportunities for empowerment in the development of digital skills, revealing underlying institutional logics and cultural mechanisms that shape these disparities. The findings provide not only a theoretical foundation for the formulation of educational policies and the optimization of technological platforms, but also offer empirical insights for the construction of future cross-national competency assessment frameworks..
Keywords— Digital competence, Information judgment, Structuration theory, Empowerment pathways

I. INTRODUCTION

With digitalization gradually embedded in social life, digital competence is no longer just a technical issue. It is about how individuals position themselves, make judgments, express their opinions, and even space for social participation in the complex information ecology. However, competence is not an innate attribute; it is a process that is continuously generated and limited by institutional arrangements, cultural environments and resource structures (Whittington, n.d.).
The problem, however, is that not everyone is on the same page. For example, in the dimension of critical knowledge, men reported higher self-assessments. This phenomenon reflected an implicit inequality in the content of education in terms of "who gets to make the judgment" (Estanyol et al., 2023). At the same time, gender, level of education, sector of employment, and level of digital development in the region all significantly affected individuals' assessment and actual mastery of digital competence. Surveys have shown that men with higher education, working in the public sector, and living in provinces with higher levels of digitization considered themselves more competent in digital skills (Nguyen et al., 2024). Such structural differences are not limited to gender or geography. In Bangladesh, despite the widespread introduction of ICT education in colleges and universities, students often struggle to acquire practical information judgment skills due to their family backgrounds and inadequate institutional resources. This generation of college students, who knew that information was important, were unable to systematically judge or critique its authenticity and credibility (Aziz & Hossain, 2024).In terms of age structure, an individual's education, gender, and social network directly determines their position in the "digital world".

Rather than rejecting technology, older adults were often passively marginalized due to a lack of service support and insufficient consideration of product design (Papí-Gálvez & La Parra-Casado, 2023).
These studies make us rethink an old question, is the digital literacy "gap" an "ability problem" for certain groups, or is it an "opportunity gap" created by external structural conditions? or is it an "opportunity gap" created by external structural conditions? And in the context of globalization, is this "gap" becoming a new form of information inequality, in which some people are doomed to be "managed by information" while others hold the right to interpret information?
Based on the above background, this paper attempts to understand and compare how gender, age and geography intertwine to affect individuals' competence in the process of judging and using digital information in the 61-country sample under the framework of "structure-empowerment-competence portrait", and to explore how How structural differences are manifested in practice through information behavioral pathways.

II. THEORETICAL FRAMEWORK

Taking Giddens' theory of structuration as a macro-point of departure, this study examined how gender structures at the national level were reproduced in institutions, cultures, and everyday practices, noting that social structures were not stand-alone frameworks, but were activated and reproduced in the ongoing practices of actors, where constraints and dynamics were always in dynamic interplay. This perspective illustrates why gender differences in digital competence across countries are highly structural and not reversible by short-term policy or educational measures.
On this basis, the study introduces the Digital Empowerment Model (DEM) as a meso-theoretical bridge. In digital platform environments, empowerment often unfolds in multiple pathways, such as technology engagement, content generation, information security awareness, and other dimensions of competence development. However, as Wang et al. (2025) pointed out in their study, the actual effect of digital empowerment was significantly affected by the external institutional environment and cultural climate, and the "competence enhancement" brought about by digital empowerment was not always linear, and may even form a new differential structure under structural constraints. Lingling and Ye (2023) further emphasized that factors such as organizational climate and identity played a moderating role between technology and individuals, and that digital empowerment is essentially a process of cognitive restructuring and resource integration.
Ultimately, the study draws upon the theory of information behavior in an attempt to understand how institutional structures and empowerment mechanisms are manifested as gender differences at the individual level through information behavior pathways. Wilson (1999) suggested that information behavior encompasses not only active information searching, but also the entire process of information reception, filtering, and use, and that these pathways could be affected by cultural acquisitions, social role expectations, and confidence in technology use. Therefore, gender differences in information and data literacy should not only be regarded as a "technology gap", but also a result of the interplay between structure-empowerment-practice.
Based on the above triple theory, this paper analyzed multi-country data to extract the potential structure of gender, age, and geographic differences in the composition of digital competence, and explored how it manifested itself in different structures of information literacy.

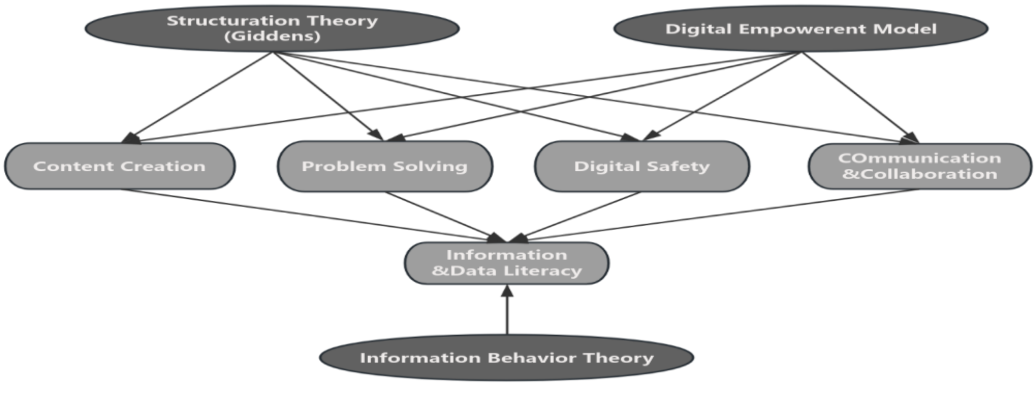

Figure 1 Theoretical Framework

III. MOTIVATION AND OBJECTIVE

Recent studies have consistently shown that structural variables such as gender, age, and geographic location not only function independently but also interact to jointly shape individuals' digital competency profiles. Digital empowerment and structural constraints are not simply opposites, but rather entangled processes. Based on multi-country data, this paper analyzed how gender, age, and urban-rural structural differences played a role in the different dimensions of digital competence, especially in the mechanisms of information judgment and use. At the same time, the study also hope to further identify and verify whether there are effective empowerment pathways under the existing structural tensions that can alleviate these structural inequalities and expand the space for individual agency.

RQ1: What is the impact of structural factors such as gender/geography/age on digital competence?

RQ2: Do structural factors such as gender/geography/age affect the ability to judge/use/create information?

RQ3: Are there empowerment pathways that mitigate these structural inequalities?

IV. RESEARCH METHODOLOGY

Using a quantitative empirical research design that combines descriptive statistics, principal component analysis (PCA), and regression modeling, this study aims to systematically identify the mechanisms by which different structural variables (gender, age, and geographic location) affect the structure of digital competence, and to explore the potential structural paths between empowerment and restriction. The research process fully combines structuration theory (Giddens, 1984), information behavior theory (Wilson, 1999) and the digital empowerment path model (Liu, 2023) to construct a theoretical to empirical model that integrates the "competency portrait construction and structural mechanism validation". A theoretical to empirical loop is constructed by combining "competency profile construction and structural mechanism validation". The core data used in this study comes from the International Telecommunication Union (ITU) Data Hub for 61 countries. The selection of specific dimensions is oriented to reflect the structure of digital human capital, covering skill mastery, cognitive literacy, collaboration habits and technology innovation potential.

Table1 The structure of digital human capital

Skill level	Individuals with above basic ICT skills in communication and collaboration Individuals with above basic ICT skills in digital content creation Individuals with above basic ICT skills in information and data literacy Individuals with above basic ICT skills in problem solving Individuals with above basic ICT skills in safety Individuals with basic ICT skills in digital content creation Individuals with basic ICT skills in information and data literacy Individuals with basic ICT skills in problem solving Individuals with basic ICT skills in safety Individuals with basic skills in communication and collaboration
collaboration	Making calls using VoIP or messaging app Participating in social networks Sending e-mails with attached files Taking part in online consultations or voting to define civic or political issues
creation	Creating electronic presentations with presentation software Uploading self/user-created content to a website to be shared Using basic arithmetic formula in a spreadsheet Using copy and paste tools within a document Using software run over the Internet for editing text documents, spreadsheets or presentations Writing a computer program using a programming language
literacy	Getting information about goods or services Reading or downloading newspapers, magazines or books Seeking health information Verifying the reliability of information found online

problem_solving	Connecting and installing new devices Doing an online course Finding, downloading, installing and configuring software Internet banking Purchasing or ordering goods or services Transferring files between a computer and other devices
safety	Changing privacy settings on your device, account or app Setting up effective security measures to protect devices and accounts

V. RESULTS

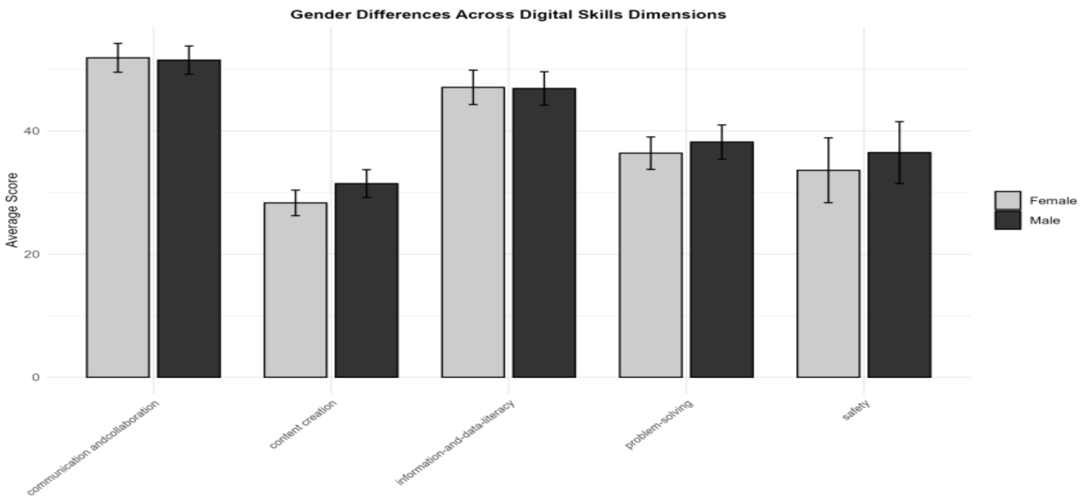

Figure 2 Impact of Gender Structural Differences on Digital Empowerment

Table 2 T-test of Gender Structural Differences on Indicators of Digital Empowerment

Indicator	Female_Mean	Male_Mean	Mean_Diff	t_value	df	p_value	Significance
communication-and collaboration	51.9	51.5	0.37	0.79	52	0.433	ns
content creation	28.3	31.4	-3.13	-6.21	48	0	***
information-and-data-literacy	47.1	46.9	0.18	0.328	52	0.745	ns
problem-solving	36.4	38.2	-1.81	-3.47	53	0.0011	**
safety	33.6	36.5	-2.88	-2.52	23	0.0191	*

From a structural point of view, the gender difference in the dimension of "content creation" is the most significant, with the average score of males (31.4) being significantly higher than that of females (28.3), with a difference of 3.13 points ($t = -6.21$, $p < 0.001$). This gap suggests that the female group may face certain barriers to expression or low frequency of use in content generation and creative expression.
Furthermore, in the "problem-solving" and "safety" dimensions, it was also observed that the mean scores of females were significantly lower than those of males, with a difference of -1.81 and -2.88, respectively, which were statistically significant ($p = 0.0011$ and $p < 0.001$, respectively). $p = 0.0011$ and $p = 0.0191$, respectively).
Taken together, although the overall gender differences are not extreme, structural gaps are still present in specific dimensions, especially in creative expression and cybersecurity-related skills, and the digital empowerment of the female population still needs to be further strengthened.

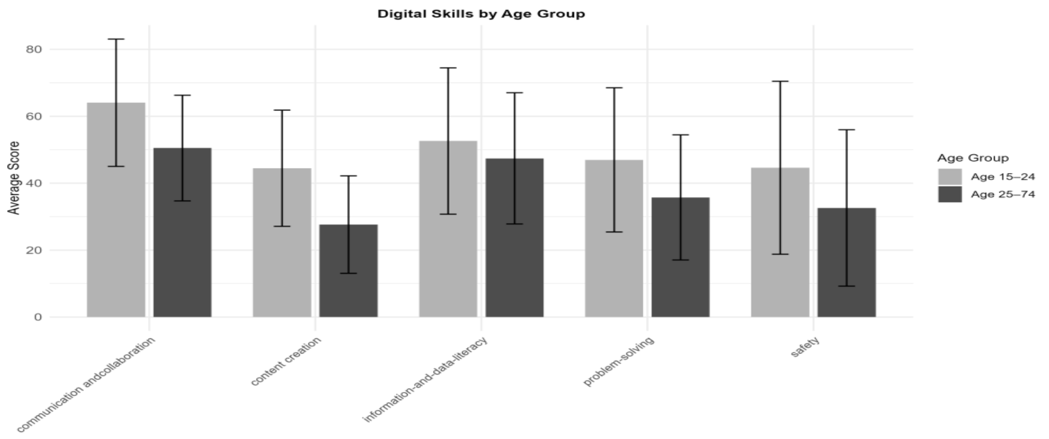

Figure 3 Effect of age structure differences on digital empowerment

Table 3 T-test of age structure differences on indicators of digital empowerment

Indicator	Younger_Mean	Older_Mean	Mean_Diff	t_value	df	p_value	Significance
communication-andcollaboration	64	50.5	13.5	8.64	47	0	***
content creation	44.5	27.6	16.8	11.2	42	0	***
information-and-data-literacy	52.6	47.4	5.19	3.48	47	0.0011	**
problem-solving	47	35.8	11.2	7.28	48	0	***
safety	44.6	32.6	12	6.04	19	0	***

Figure 3 illustrates the distribution of the scores of the different age groups on the five dimensions of digital skills.

Combined with the results of the t-test, it is clear that the younger group (15-24 years old) has significantly higher scores than the older group (25-74 years old) on all the digital skills dimensions, and all the differences are statistically significant ($p < 0.01$).

The dimension with the most significant difference is 'content creation', where young people scored an average of 44.5 compared to 27.6 for the older group, a difference of 16.8 points ($t = 11.2$, $p < 0.001$). This result reflects that young people have an absolute advantage in content creation activities such as creative expression and graphic video generation, which is highly correlated with their lifestyle habits of being exposed to multimedia platforms and participating in short-video production since they were young. There is still a significant disadvantage in operation proficiency.

In summary, age structure has a significant impact on digital empowerment, and young people have a clear advantage in skills such as content creation, communication and collaboration, and network protection.

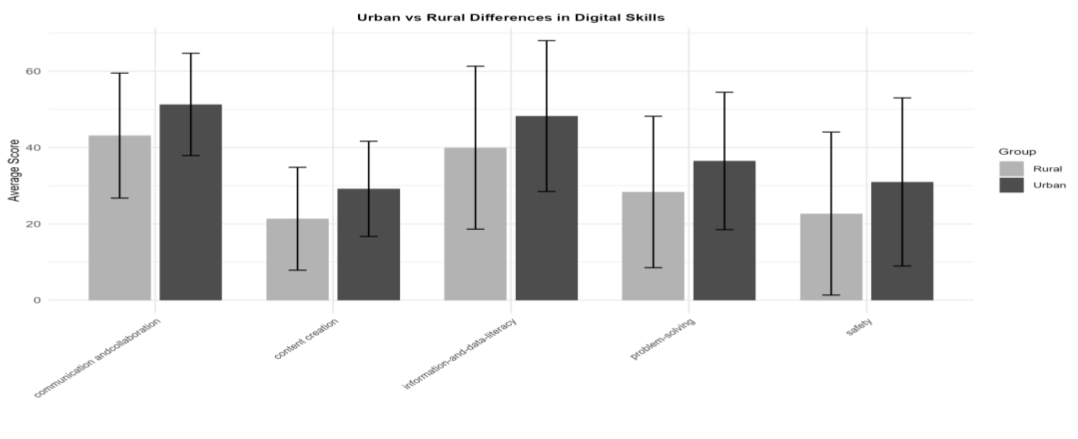

Figure 4 Impact of geographic structural differences on digital empowerment

Table 4 T-test of geographic structural differences on various indicators of digital empowerment

Indicator	Urban_Mean	Rural_Mean	Mean_Diff	t_value	df	p_value	Significance
communication-andcollaboration	51.3	43.2	8.18	7.69	40	0	***
content creation	29.2	21.4	7.84	11.5	37	0	***
information-and-data-literacy	48.2	40	8.27	7.69	40	0	***
problem-solving	36.5	28.4	8.13	8.59	41	0	***
safety	31	22.7	8.28	6.45	16	0	***

Figure 4 shows the difference between the mean scores of the urban and rural groups on the five core digital skill dimensions.

Combined with the results of the t-test, it can be seen that the urban group performs significantly better than the rural group in all the digital skills dimensions, with all differences reaching the highly significant level of $p < 0.001$.

In the dimension of communication and collaboration, the average score of urban residents is 51.3, which is significantly higher than that of rural residents, which is 43.2 ($t = 7.69$, $p < 0.001$). This suggests that the urban population is more capable of using digital technologies for online collaboration, social interaction, and organizational coordination.

Overall, these results fully reveal a systematic imbalance in the structure of digital skills between urban and rural areas. This finding suggests that policymakers should prioritize future digital literacy interventions to focus on rural groups, especially in improving their hands-on skills in content creation, information literacy and digital security.

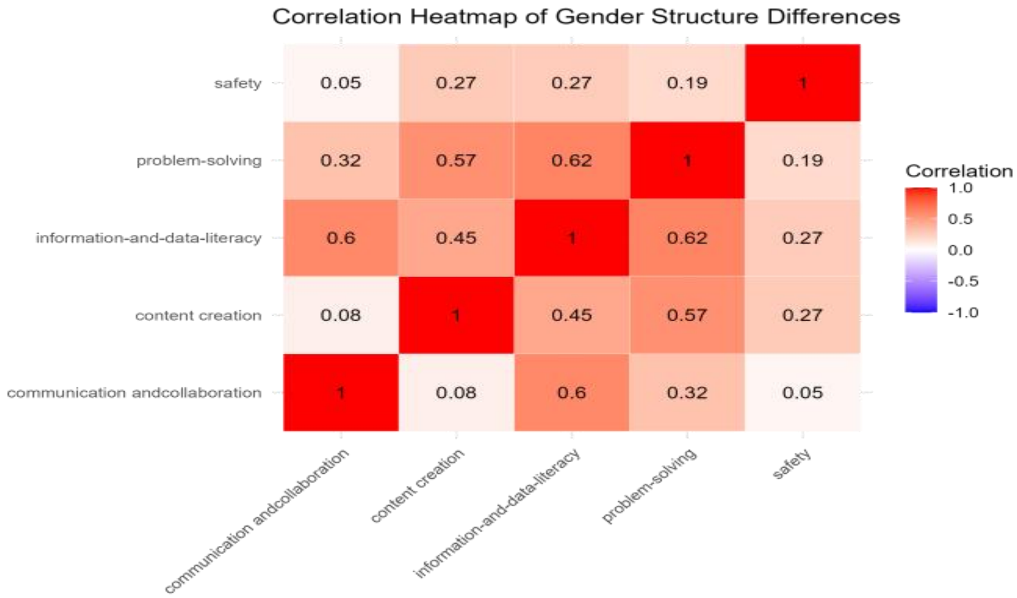

Figure 5: Correlation analysis of gender structure dimensions

The correlation analysis shows that there are significant but heterogeneous structural linkages between different digital competence dimensions. Among them, “information and data literacy” has the strongest correlation among all variables, especially with “problem solving ability” ($r = 0.62$) and “communication and collaboration ability” ($r = 0.60$). ($r = 0.62$) and “communication and collaboration skills” ($r = 0.60$), suggesting that it may have the attribute of ‘bridge’ or “mediator” in the digital competence network. On the other hand, the overall correlation of “digital security” is weak, and only moderately correlated with “content creation” and “information literacy”, which may imply that the formation mechanism of security is more independent or related to external structural variables (e.g., “digital security”), and that the correlation between “content creation” and “information literacy” is moderate. This may imply that the formation mechanism of security is more independent or associated with external structural variables (e.g. institutional trust, platform design).

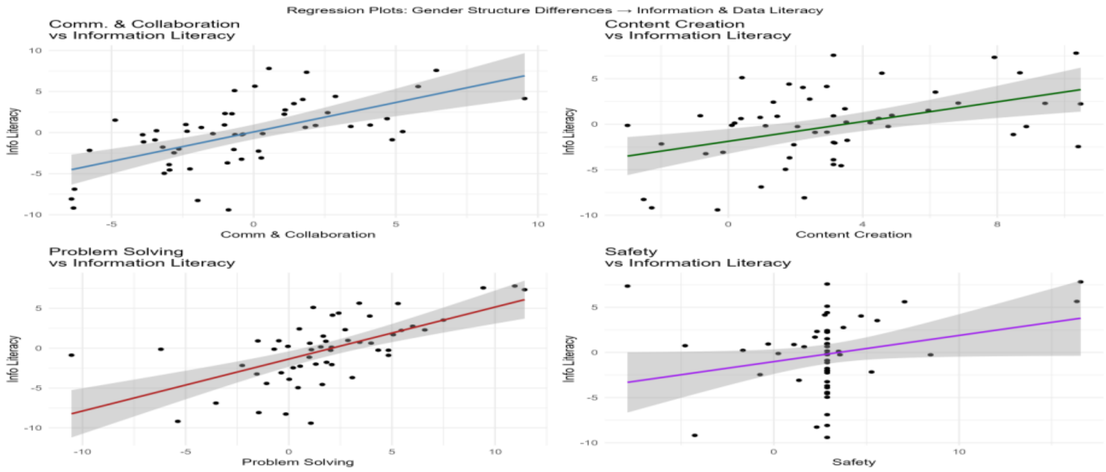

Figure 6 Regression of Digital Competency Indicators on Information Literacy by Gender Structural Gap

From the visualization of the four regression models, the gender structural gap in communication and collaboration competencies has the strongest explanatory power (steepest slope and tightest fit bands) in predicting gender differences in Information and Data Literacy, suggesting that the communication dimension may be a core variable in the information literacy empowerment pathway. This trend is consistent with the "collaborative digital empowerment path" proposed by Wu et al. (2025) . In contrast, the digital security dimension showed a positive trend, but the predictive power was weak, suggesting that gender differences play a more marginal role in the construction of information literacy.

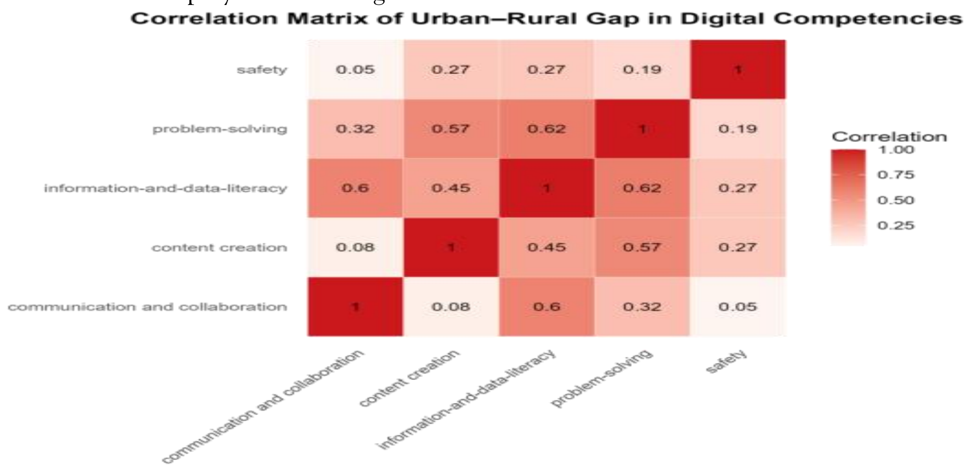

Figure 7 Correlation analysis of geographical structure dimensions

Overall, there is a moderate positive correlation between the dimensions, indicating a certain synergistic trend in the development of digital skills in the personal competence structure. Among them, the correlation between "information-and-data-literacy" and "problem-solving" is the highest (r = 0.62), which indicates that good information literacy is often the key to effective problem-solving in today's digital environment. In today's digital environment, good information literacy is often a prerequisite for effective problem-solving. Individuals facing complex problems often need to accurately retrieve, filter, and understand information before developing solutions, so these two dimensions tend to go hand in hand in terms of competency performance.

In contrast, the correlation between the "safety" dimension and other skills is relatively low, especially with "communication and collaboration" (r = 0.05) and "content creation" (r = 0.05). "content creation" (r = 0.27). This result suggests that digital security awareness and practice may depend more on individual experience accumulation, situational awareness, and external education than on the natural transfer of skills.

In summary, the structure revealed in Figure 7 provides a theoretical basis for the subsequent construction of a digital skills classification model or cluster analysis, as well as an empirical reference for determining the order of skills focus and paths in teaching and training. Especially in improving "safety" skills, special intervention paths should be adopted to avoid its marginalization in the overall improvement.

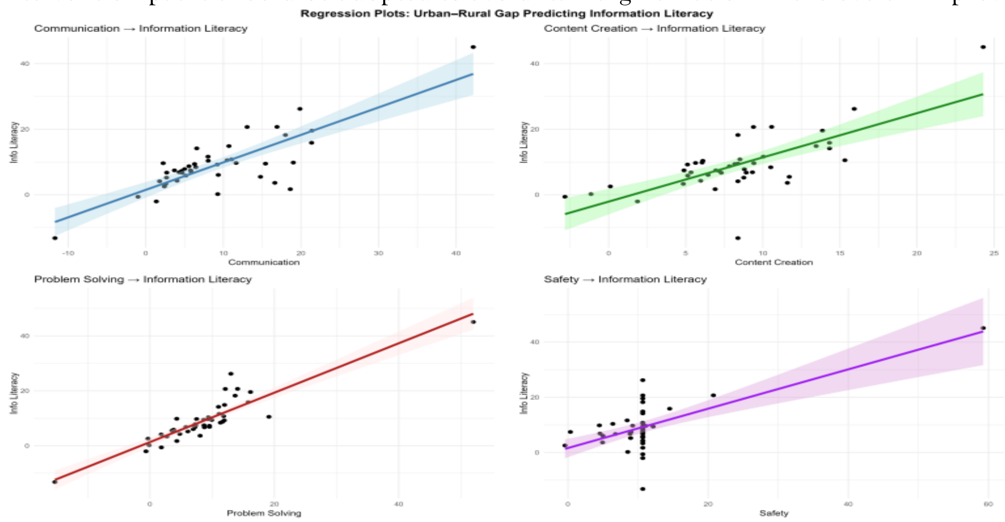

Figure 8: Regression of each digital competency indicator with information literacy under geographic structure differences

This set of regression plots demonstrates the predictive effect of the four key digital skills on information literacy (IL) in both urban and rural groups. The overall trend is clear: communication and collaboration, content creation, problem solving, and digital security all show significant positive predictive effects on information literacy.

Among them, the linear relationship between "problem-solving" and "information literacy" is the strongest, with the largest slope and the highest degree of fit, suggesting that the improvement of information literacy relies heavily on the ability of This indicates that information literacy relies heavily on an individual's ability to handle complex digital tasks. Secondly, "communication" and "content creation" also show a stable positive correlation, emphasizing the role of expression and communication in supporting information understanding and utilization in the digital environment.

The regression line for the dimension of "safety" is relatively flat, with a slightly dispersed scatter distribution, which is still predictive, but with relatively low significance and explanatory power, suggesting that although safety awareness is important, it may be an indirect or lagging influence in the information literacy structure of urban and rural groups.

Overall, this set of regression results highlights the status of information literacy as the core pivot of digital competence, and also reveals the differences in the functional weights of different skill dimensions in the context of urban-rural differences.

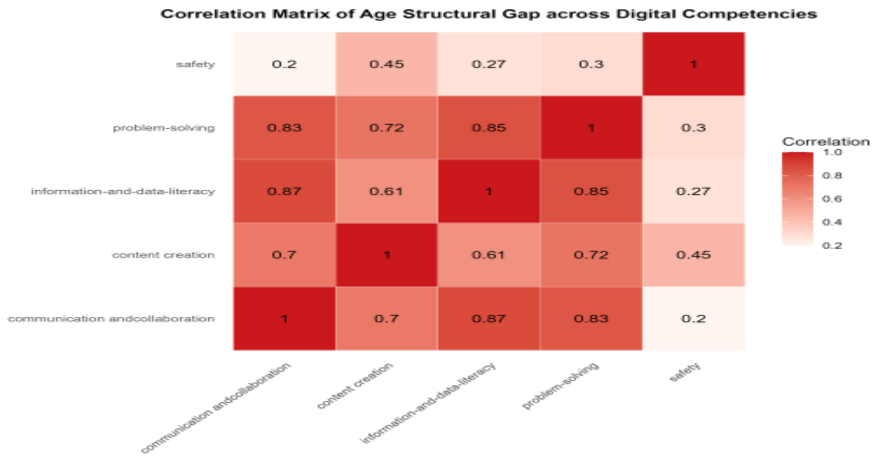

Figure 9: Correlation analysis of age structure dimensions

This correlation heat map shows that there is a clear synergistic structure among the dimensions of digital competence, and information literacy is the core link connecting communication, collaboration and problem solving, which is highly correlated with each other and constitutes the "backbone system" of the digital practice competence.

This principal component analysis extracted the potential common factors among the structural differences of the four digital competencies (excluding information literacy). The results show that the first principal component (PC1) explains most of the common variability among the four variables, with problem-solving (0.558), content creation (0.548), and communication & collaboration (0.540) contributing the most to this principal component, suggesting that the variance of these variables in the urban-rural or age structure is not significant. patterns of differences in urban-rural or age structure are highly consistent. In contrast, the weight of safety (0.311) is lower but still positive, suggesting that the trend of its differences is generally consistent with the other competencies in terms of direction but relatively independent. Thus, PC1 can be regarded as a "structural variance factor for supportive digital competencies" that represents the degree of overall structural inequality. It provides a more robust and concise indicator basis for subsequent regression modeling and cross-country comparative analysis.

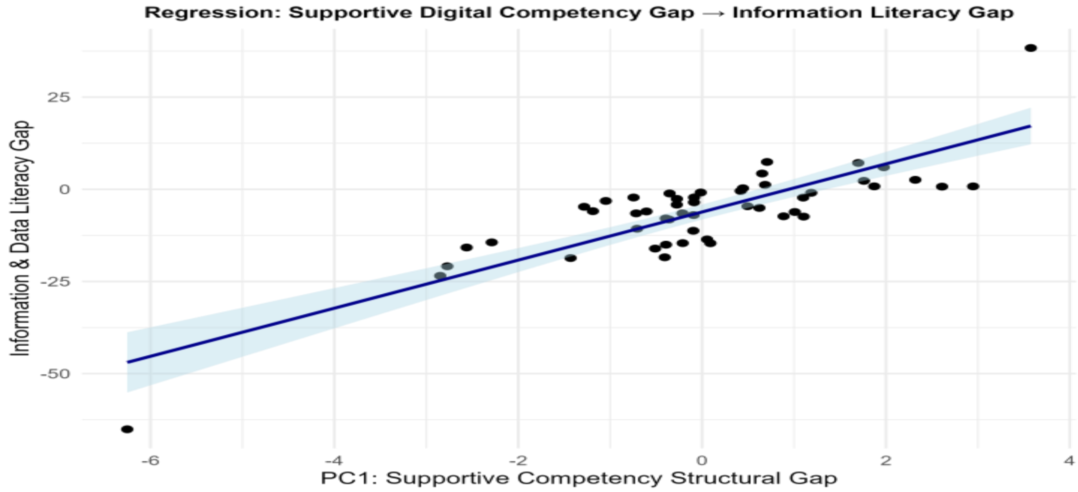

Figure 10: Regression of Digital Competence Indicators and Information Literacy under Age Structure Differences

It can be seen from the figure that the residuals are roughly evenly distributed along the diagonal, with no systematic deviation or "funnel-like" diffusion trend, indicating that the model basically meets the assumption of homoskedasticity in linear regression. Meanwhile, there are no obvious extreme values or abnormal aggregation of data points, which supports the stability and predictive validity of the model. Overall, this graph indicates that the constructed linear model fits well and the residuals are reasonably distributed, further suggesting that age-structural differences are influencing information literacy competence.

VI. DISCUSSIONS

It is clear from the results that "capabilities" do not flow equally across structural contexts. Whether in terms of gender, age, or rural/urban structure, differences do not exist by chance, but are the result of a continuous production of institutional and cultural configurations over a long period of time.

Giddens (1984) has pointed out that social structures do not exist statically, but are maintained and reproduced in the repetitive practices of actors, which is deeply reflected in this study. For example, women's score disadvantages in "content creation" and 'safety' do not stem from physical or psychological "natural deficits", but rather from the logic of platform design, educational discourse, and gender role expectations. It is a combination of platform design logic, educational discourse, and gender role expectations. As Lo et al. (2024) pointed out, gender blindness in the development of teachers' digital literacy often leads to a lower level of acceptance of technological participation among female users, who are thus left behind on the "empowerment track". It is also worth noting that the younger age groups are ahead across the board in almost all dimensions. This advantage seems to be due to the "starting line" of digital natives, but it also implies a tendency for "skill empowerment" to be more and more experience-based and platform-accustomed, and Park et al. (2021) pointed out through bibliometric analysis that digital literacy has evolved from the early "literacy skills" to "literacy skills". And through their bibliometric analysis, pointed out that the evolution of digital literacy has shifted from early 'literacy' to 'participatory competence', which is clearly more dependent on media experiences in life trajectories. This trend is also confirmed by Pinto et al. (2023), who emphasize the stratification of "data literacy" not only in terms of technological mastery, but also in terms of an individual's ability to understand the meaning of technology.

The urban-rural divide reveals a more profound problem of "structural reproduction". Urban groups are at the forefront of information comprehension, communication and collaboration, and content creation, suggesting that "digital empowerment" tends to occur first among groups with more concentrated resources and access to existing resources. This finding echoes the study by Wu et al. (2025), who analyzed of the developmental stages of digital literacy - the so-called "secondary digital divide", which is no longer about "whether there is internet or not", but rather about "who can use it well". " Lingling and Ye (2023) further pointed out that digital empowerment is not a single linear process, but rather a process of constant regulation and modification between technological interventions, identities and social structures. moderated and modified.

From the results of the regression model, it is clear that both communication and collaboration, problem solving and content creation almost always form intersections around information literacy. This finding coincides with model of information behavior as a practical pathway embedded in the life world (Wilson, 1999a), moderated by motivation, context, strategy, and available resources, with the structural variables of gender and geography often acting indirectly on the skill pathway through cognitive confidence, role expectations, and experiential exposure.

In Giddens' theoretical context, this difference should not simply be viewed as 'unskilled', but rather as a form of 'passive agency' within structural constraints. That is to say, although individuals have the desire to participate, they are restricted by institutional "rule allocation" and "resource scheduling", so that the "empowerment" that they can realize in digital space presents a hierarchical structure. As Shi and Wan (2024) pointed out in their study of the digitization of education in China, while policy impetus is important, if the persistence of structural constraints is ignored, the "universalization" of digital technologies may instead magnify the consequences of unequal empowerment.

VII. CONCLUSIONS

The path of digital empowerment is never a smooth road spread evenly, but a complex trajectory defined by a combination of access, usage habits, identity perceptions and institutional support. As Lingling and Ye, (2023) pointed out, digital empowerment was not just about technological empowerment, but also a process of negotiating practices under the interaction of cognition and environment. In terms of information literacy, it plays an important role across multiple dimensions, not only influencing how individuals search for and process information, but also permeating their strategies of expression, judgment, and security. This echoes Bates and Wilson's early definition of information behavior as "cognitive scheduling embedded in practice" rather than isolated technical actions.

If future research and policy design is to promote digital equity, it must simultaneously address two dimensions, first, the adjustment of structural conditions, including the rebalancing of platform design, education policy, and cultural discourse; and second, the more detailed identification of the ability profiles of different groups, avoiding a one-size-fits-all approach to setting empowerment paths. In future research, cross-cultural studies can be further attempted.

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