Development and Validation of the Perception of Interdisciplinary Research Collaboration (PIRC) Scale

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Abstract

Interdisciplinary research collaboration is crucial for addressing complex global challenges, and measuring researchers' perceptions of it is vital. The Perception of Interdisciplinary Research Collaboration (PIRC) Scale was meticulously developed and validated in this study to enable researchers to assess these perceptions comprehensively. The scale was developed in line with the team science theory. This cross-sectional study involved concept analysis, face and content validity, item pretesting, and pilot testing. A panel of eight specialists from relevant fields meticulously reviewed the items in the instrument, and their inputs and suggestions were followed to refine the instrument, resulting in a 64-item questionnaire. A sample of 1,932 academic staff members with interdisciplinary research experience were selected from six universities in South-South Nigeria for a pilot study. A simple random sampling technique was employed in selecting these participants. Exploratory factor analysis yielded six underlying dimensions within the PIRC Scale, such as: "challenges of Interdisciplinary Disciplinary Research (IDR) collaboration," "IDR collaborative experiences," "motivations for IDR collaboration," "benefits of IDR collaboration," "career impact of IDR collaboration," and "IDR team dynamics." Confirmatory factor analysis confirmed this structure and revealed the bifactor model as the best-fitting model over the unidimensional, oblique and higher-order models. Utilising the Fornell-Larcker approach, strong convergent and discriminant validity was established across all dimensions, with Average Variance Extracted (AVE) above .50 and the square root of the AVE for all factors being greater than the correlation coefficients of each factor with other factors. Cronbach's alpha and McDonald's omega values exceeded the acceptable threshold of 0.70, with item-total correlation analyses further supporting the reliability of each sub-scale and the overall instrument. In conclusion, the PIRC scale can be valuable for researchers, institutions, and policymakers to assess and enhance interdisciplinary research collaboration. It can empower stakeholders to obtain useful information about researchers' perceptions of interdisciplinary research, promote effective collaboration, allocate resources efficiently, and foster innovation.

Keywords: Academic collaboration, career impact, perception assessment, psychometric validation, research benefits, scale development.

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INTRODUCTION

Research is an action-oriented process involving a series of systematic procedures to create knowledge, identify problems and seek ways of dealing with such issues to improve man's understanding of the environment and other phenomena (Odigwe et al., 2020; Owan & Bassey, 2019). Interdisciplinary research is a method of research by a group of people that coordinates information, data, strategies, apparatuses, viewpoints, ideas and theories from two or more disciplines to propel major understanding or to take care of issues whose solutions are beyond the extent of a single discipline. Klaassen (2018) describes interdisciplinary research as combining methods, knowledge, skills, theories, and perspectives from different disciplines to foster innovative solutions and advance knowledge in uncharted problem areas. Interdisciplinary research differs from multidisciplinary research, where specialists work independently on various parts of an expansive issue (Choi & Pak, 2007). Interdisciplinary research can likewise be distinguished from transdisciplinary research, where specialists absorb disciplinary-explicit theories and ideas to care for an issue while limiting the isolation of the different disciplines (Fuqua, 2012).

Interdisciplinary research has gained prominence, with institutional leaders championing it, resulting in a rise in cross-disciplinary dissertations in recent years (Kniffin et al., 2021). It has been suggested that interdisciplinary research can bring greater benefits and influence (Bromham et al., 2016; Leahey et al., 2017). Since interdisciplinary research exceeds the regular scope of a discipline, numerous specialists and researchers across the globe accept that interdisciplinary research can resolve complex issues that solitary discipline research cannot (Kulkarni, 2015). For instance, the field of computer science has been significantly influenced by interdisciplinary research, enabling the resolution of complex problems (Chakraborty, 2017). In addressing complex environmental issues, interdisciplinary research is often essential for developing a comprehensive understanding of integrated systems (Bark et al., 2016).

Consequently, interdisciplinary research has gained much attention recently and has made more extensive social and economic contributions (Feng & Kirkley, 2020; Urbanska et al., 2019). The underlying justification for IDR activities is traceable to an undeniably shared view among scholars and policymakers that some problems dwell beyond a single discipline and need multiple efforts, skills, techniques and expertise. Another reason for IDR is the need to take care of the progressively complex issues of society (Mainzer, 2011). Moreover, interdisciplinary research is increasingly being recognised and supported by funding agencies and institutions. In an instance, when scholars were solicited to submit cases from research that had a huge effect outside the scholarly community to the 2014 Research Excellence Framework (REF), 80% were discovered to be interdisciplinary (Kulkarni, 2015; Pedersen, 2016). Also, the Tertiary Education Trust Fund (TETFund) calls for the submission of grant proposals (from 2020 to date) and places serious emphasis and priority on transdisciplinary, multidisciplinary and interdisciplinary teams and projects (Okon et al., 2022).

However, despite this attention, there are limited instruments available to gauge the perception of researchers regarding interdisciplinary research collaborations. Thus, assessing researchers' perceptions regarding interdisciplinary research collaborations faces notable challenges due to the absence of standardised tools measuring the dynamic nature of interdisciplinary endeavours. The lack of such tools with acceptable psychometric properties hampers our ability to consistently determine the level of success or impact of interdisciplinary projects, leading to varied and sometimes biased results. Besides, the need for an instrument to measure interdisciplinary research has since been recognised by other researchers (e.g., Begg et al., 2014; Brown et al., 2019; Carr et al., 2018; Handtke & Bögeholz, 2019; Tate et al., 2018). Moreover, other scholars have also highlighted the dearth or lack of instruments that can effectively assess and monitor the characteristics of interdisciplinary research teams (Porter et al., 2007; Rinia, 2007; Wagner et al., 2011). Furthermore, the systematic review conducted by Lakhani et al. (2012) indicated a need for an instrument to be developed to assess and monitor the characteristics of effective interdisciplinary research teams. To them, "such an instrument can provide information about interdisciplinary team attributes and support team self-evaluation by identifying areas of strength and weakness" (Lakhani et al., 2012, p. E264). However, the effectiveness and productivity of interdisciplinary teams can be challenging to measure due to the lack of contextual instruments revealing the details and the complexity of interdisciplinary work (Nancarrow et al., 2013).

Therefore, developing an instrument to measure factors contributing to interdisciplinary team effectiveness and productivity is essential (Nancarrow et al., 2013). In addition to measuring team effectiveness and productivity, indicators of interdisciplinary research in such an instrument should also focus on collaborative processes within research teams (Tate et al., 2018). For these reasons, this study was conceived to develop and psychometrically validate the PIRC Scale. Specifically, the study was aimed at:

1. establishing the content and face validity of the PIRC scale;
2. assessing the dimensionality and internal structure of the PIRC scale;
3. determining the convergent and discriminant validity of the PIRC scale;
4. determining the reliability of the PIRC scale.

Thus, the PIRC scale can contribute to interdisciplinary research by offering a systematic and comprehensive framework for assessing researchers' perceptions of collaboration dynamics. Its utility spans various dimensions, including informing strategic decision-making for funding agencies and institutions, guiding individual researchers' professional development, and cultivating a positive interdisciplinary culture. The scale facilitates benchmarking and program evaluation, enabling continuous improvement in interdisciplinary research initiatives. Its adaptability to changing trends ensures ongoing relevance, while its educational applications allow for tailored approaches to interdisciplinary training. The PIRC Scale is a versatile and valuable tool that enhances understanding and actively contributes to the success and advancement of interdisciplinary collaboration across diverse research settings.

A Review of Previous Instruments

A framework for evaluation has been proposed to gain insight into interdisciplinary research and education programs (Carr et al., 2018). This framework provided valuable guidance in assessing the impact and effectiveness of interdisciplinary programs, including research teams. Similarly, some instruments have been constructed to identify factors contributing to interdisciplinary team effectiveness and their level of productivity. Some of these instruments include the Myers-Briggs Type Indicator (Myers-Briggs et al., 1985), the Kolb Learning Style Inventory (Kolb, 1984), the Conflict Mode Instrument (Kilmann & Thomas,1975) and the Bolman and Deal Leadership Orientation Instrument (Bolman & Deal, 1991).

The Myers-Briggs Type Indicator (MBTI) is a widely used instrument that assesses personality preferences and provides insight into how individuals interact and communicate within a team (Nancarrow et al., 2013). The Kolb Learning Style Inventory (LSI) measures individuals' preferred learning styles, and how they approach problemsolving and decision-making within a team (Körner, 2010). The Conflict Mode Instrument (CMI) is a tool that assesses individuals' preferred approach to conflict resolution in an interdisciplinary team (Cassarino et al., 2018). Conflict is inevitable in interdisciplinary teams, and understanding how team members handle conflict can help facilitate productive discussions and prevent conflicts from escalating (Arop et al., 2018). The Bolman and Deal Leadership Orientation Instrument (LOI) measures the leadership styles and orientation among interdisciplinary teams (White et al., 2013). Effective leadership is crucial for team effectiveness (Owan et al., 2022c), and this instrument can help identify leadership strengths and areas for development within the team.

However, none of these measures employed a theoretical framework to organize the concepts being assessed, nor have there been any psychometric evaluation of these measures (Lakhani et al., 2012). Therefore, a reliable and valid measure of staff's perception towards engaging in interdisciplinary research collaboration is needed to enable researchers and research teams to focus on specific areas of improvement. Such a tool would not only enhance the productivity and maturity of interdisciplinary teams, but will also optimise resource allocation, improve research outcomes, promote knowledge transfer, support team development, and aid in career advancement (Butt & Dimitrijević, 2022; Kelly et al., 2023). It will also represent an investment in the future of science and innovation, facilitating effective collaboration in tackling some of society's most pressing issues (Cairns et al., 2020; Hesjedal, 2023; Moirano et al., 2020; Owan et al., 2023a; Scholz, 2020).

Theoretical Framework

Bridging the gaps from the previous instruments, the present study derives root from the Team Science Theory (TST). The TST has evolved as a theory in response to the changing nature of scientific research and the recognition that many contemporary challenges require collaborative and interdisciplinary approaches. Nevertheless, early works of scholars, such as Paul (1955), Foster (1987), Klein (1990), and Rosenfield (1992) laid the groundwork for this theory. The theory was further amplified by the writings of Gray (2008), Klein (2008) and Cooke et al. (2015). The TST revolves around the idea that contemporary scientific research is increasingly being carried out by cross-disciplinary teams rather than individuals in specific fields (Kessel & Rosenfield, 2008). This theory strongly emphasises collaboration, advocating for the assembly of experts from diverse fields to tackle complex problems collectively (Cavanaugh et al., 2021). The theory underscores the limitations of relying solely on individual expertise and champions the integration of viewpoints and methodologies from various disciplines.

At its core, TST promotes an interdisciplinary research approach, acknowledging that multifaceted issues demand a comprehensive understanding that can only be achieved by combining knowledge and skills from different domains (Knapke et al., 2021). This holistic perspective encourages researchers to look beyond the boundaries of their disciplines and consider the interconnected factors influencing a given phenomenon. An important outcome of adopting the TST is the potential for increased innovation (Bennett & Gadlin, 2012; Rosenfield, 1992). Collaborative efforts are seen as catalysts for creativity, as the synergy of diverse expertise within a team can generate novel ideas and approaches that might not emerge from individual endeavours (Owan et al., 2023a). This collaborative model also aims to streamline resource utilization, avoiding duplication of efforts and maximizing the impact of available resources (Tebes & Thai, 2018). Furthermore, TST recognizes the need for effective team dynamics and communication within interdisciplinary teams (Klein, 2014). It emphasises the importance of team members appreciating and understanding each other's expertise and perspectives, fostering an environment conducive to successful collaboration (Hall et al., 2018). The theory also has broader implications for shaping policies and practices in research institutions, advocating for structures and incentives that support collaborative efforts.

While TST presents a promising framework for addressing complex scientific challenges, it acknowledges the existence of challenges and barriers associated with interdisciplinary collaboration. Differences in language, methodology, and research culture can pose obstacles, necessitating the development of strategies to overcome these challenges and facilitate successful collaboration (Dusdal & Powell, 2021; Lawrence et al., 2022). Additionally, the theory prompts a re-evaluation of traditional evaluation criteria to appropriately assess the success and impact of interdisciplinary research (Bruzzese et al., 2020; Sun et al., 2021). Therefore, the researchers' decision to ground this study in the TST proves highly relevant as it provides a comprehensive framework for developing and validating the PIRC Scale. The core principles of TST, emphasizing multidisciplinary collaboration, recognition of the limitations of individual expertise, and the promotion of innovative, research, align seamlessly with this study's objectives. The PIRC scale emerges as a tool designed to capture the multidimensional aspects of collaborative efforts, fostering effective team dynamics, communication, and challenges identified by TST in interdisciplinary collaboration. By integrating TST, this study addresses the specific goals of PIRC scale development. It contributes to the paradigm shift towards collaborative and interdisciplinary approaches in scientific research, reflecting the ongoing evolution of scientific inquiry.

METHODS

Research Design

The researchers adopted a cross-sectional survey research design in developing and validating the PIRC scale. This design allows for the collection of data at one point in time from the participants. The design also allowed the researchers to follow several steps in developing and validating the PIRC scale. These steps include concept analysis, content validity, pretesting of items, pilot testing, extraction of factors, a test of dimensionality, test of reliability, test of validity, and the development of scoring and interpretation guidelines.

Concept of Interdisciplinary Research Collaboration

The concept of interdisciplinary research collaboration refers to the integration of knowledge and approaches from multiple disciplines to address complex problems (Petri, 2010). It involves the collaboration and cooperation of researchers from different disciplines to achieve common goals (Feng & Kirkley, 2020). An instrument needs to be developed to measure the perception of interdisciplinary research collaboration. The instrument should capture participants' perceptions of interdisciplinary collaboration, including their attitudes, beliefs, and experiences. It should assess factors such as the willingness to engage in interdisciplinary research, the importance of interdisciplinary work, and the perceived barriers and benefits of collaboration (Kirby et al., 2019). The researchers developed a conceptual framework (Figure 1) comprising several key dimensions based on information deduced from the literature. These dimensions encompass the benefits and advantages of interdisciplinary collaboration, the challenges researchers encounter in such endeavours, the dynamics within interdisciplinary teams, the career implications of engaging in interdisciplinary research, the actual experiences of researchers in collaborative projects, and the motivations that drive individuals to embark on interdisciplinary research collaborations. This framework provides a comprehensive lens through which researchers can gauge and evaluate the multifaceted nature of interdisciplinary collaboration and the perceptions associated with it.

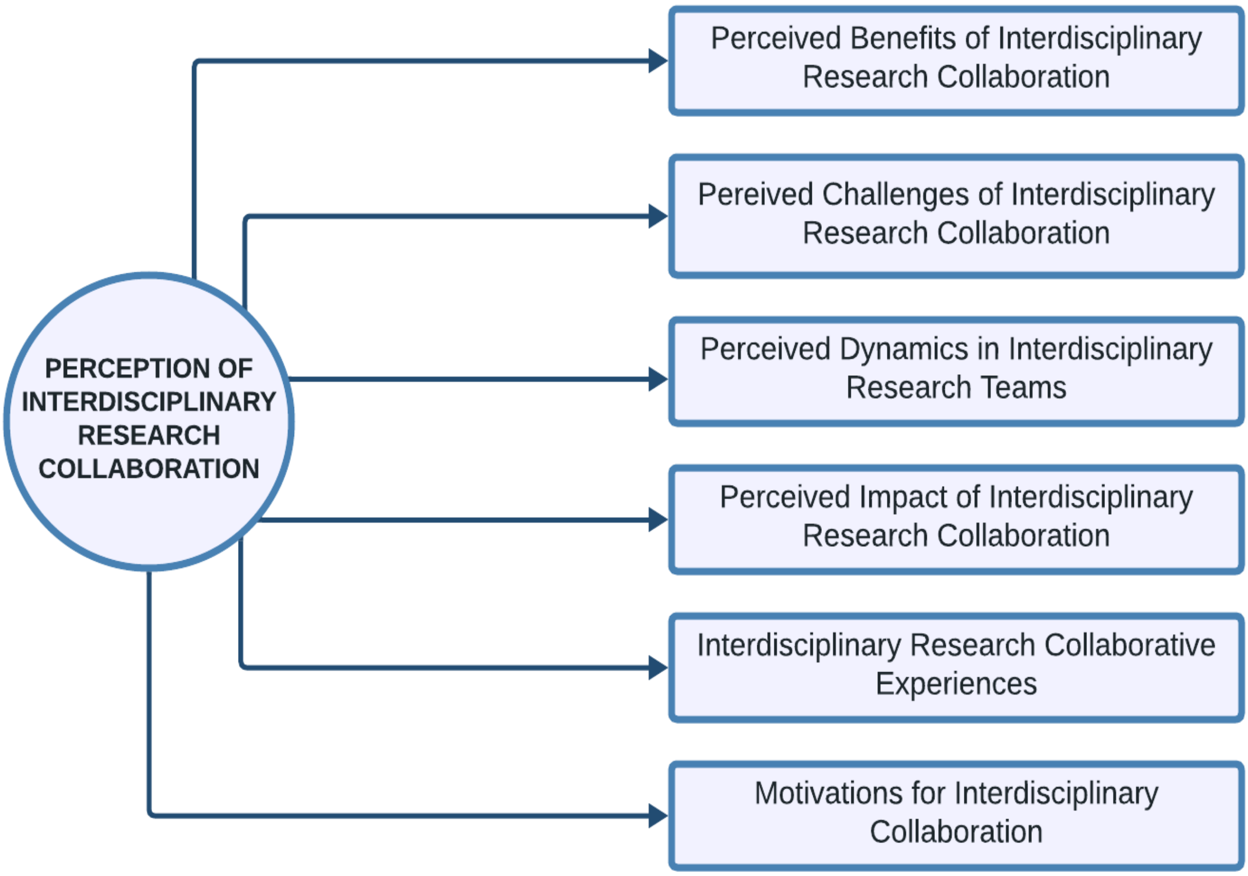

Figure 1: Conceptual framework of perception of interdisciplinary research collaboration scale
Source: Authors' elaboration.

The Perception of Interdisciplinary Research Collaboration (PIRC) Scale

The PIRC scale is a self-report questionnaire developed to measure the perception of interdisciplinary research collaboration among researchers, academics, scholars and individuals engaging in research activities that transcend disciplinary boundaries. Through an extensive review of the literature, coupled with expert opinions from scholars with relevant experience, an initial pool of 80 items was developed. The items were worded to allow respondents to indicate (by ticking) the extent to which they agreed or disagreed with the items. The Likert scale ranged from 1 to 4, with the following response options: Strongly Disagree, Disagree, Agree and Strongly Agree.

Content Validity Procedure

To establish the content validity of the PIRC scale a panel of eight experts was formed. The experts were drawn from fields such as Educational Research, Measurement and Evaluation (n = 5), and Educational Psychology (n = 3). The ages of the experts ranged from 34 to 57 years, with work experience ranging from 9 to 22 years. The team of experts include three full professors and five associate professors. Five assessors were males and three were females. Based on their diverse expertise, these experts independently reviewed and assessed the instrument items, on the basis of relevance, clarity, simplicity, and ambiguity. The experts assigned ratings for each item, reflecting their varied perspectives and substantial experiences. Ratings were done on a scale of four across all the criteria. A total of 57 items that achieved a sufficiently high Item-Content Validity Index (I-CVI) of 0.78 or above on each of the four criteria were retained, following the recommendations of Lawshe (1975). However, seven items were revised, based on the remarks and suggestions of the experts since their I-CVIs ranged from 0.67 to 0.74. However, 16 items were dropped for having very weak I-CVIs (below .50), reducing the length of the PIRC scale to 64 items.

Pretesting of Items

The instrument underwent a pretesting phase to enhance the items' clarity, comprehensibility, and relevance. This was done through a focus group discussion with a sample of potential respondents (Tripp & Shortlidge, 2020). The pretesting of instrument items involved 20 university lecturers with extensive interdisciplinary research experience recruited from two public universities in Nigeria. A purposive sampling strategy was adopted to recruit the 20 participants to represent various academic disciplines and backgrounds. The participants engaged in a focus group session guided by an experienced moderator and facilitator, both well-versed in interdisciplinary research dynamics. Informed consent was diligently obtained to ensure that there was voluntary participation. The researcher also assured them of confidentiality, promising them that all collected data would be anonymised. During the structured focus group discussion, participants were presented with the revised version of the 64-item PIRC scale and encouraged to provide candid feedback. They highlighted aspects of the items that they found confusing, unclear, or irrelevant, following the probing questions asked by the facilitator. The resulting feedback aided in item revisions, ensuring that the instrument effectively measured the perception of interdisciplinary research collaboration.

Pilot Testing

For the pilot testing of the PIRC scale, the researcher selected a sample of academic staff with interdisciplinary research experience from six universities in South-South Nigeria. This choice ensured that only respondents with the necessary experience participated (Woosnam & Norman, 2009). Power analysis guided the sample size determination to balance meaningful feedback and pilot study manageability (Teresi et al., 2021) (Cohen, 1988; Westland, 2010). An a priori sample size calculator for structural equation models developed by Soper (2023) was used. The desired statistical power was set at 80%. With six latent variables and 64 observed variables, a significance level of 0.05 alpha was set. The power analysis indicated a minimum sample size of 1,989 participants was required to detect an effect size of 0.50. A simple random sampling procedure was followed in the actual selection of participants.

Ethical considerations and data collection

The study received prior approval from the institutional review board of the University of Calabar, with approval number UCA-IRB-2023-029. Informed consent was obtained from all selected academic staff members, who were fully informed about the study's purpose and the voluntary nature of their participation, with the right to withdraw at any point. Additionally, the researcher ensured that the survey was conducted onsite at each university. This arrangement guaranteed that respondents had access to the necessary resources and support to accurately complete the PIRC scale (Fappa et al., 2016). Copies of the instrument were physically administered to the 1,989 selected academic staff members at their respective institutions. During the survey, participants were encouraged to provide feedback on each item of the scale through open-ended questions. Upon completion of the data collection process, a total of 1,932 completed copies of the questionnaire were recovered and found useful, suggesting an attrition of 57 copies (3% attrition rate). Subsequently, the data collected were analysed to establish the psychometric properties of the PIRC scale. SPSS version 27 and AMOS version 26 statistical software packages were used for data analysis.

RESULTS

Extraction of Factors

The dataset, comprising responses to the 64-item instrument, underwent examination to ensure data quality. Checks for normality, outliers and multivariate outliers were conducted using histograms, boxplots, and Mahalanobis distance tests (Hair et al., 2019; Tabachnick & Fidell, 2019). Three multivariate outliers were detected by the Malahanobis distance test and deleted from the dataset, further reducing the number of cases from 1,932 to 1,929. After that, Exploratory Factor Analysis (EFA) was performed to determine the structure of the instrument and the relationships between its items (Ekpenyong et al., 2023; Owan et al., 2022a; Owan et al., 2023b). Principal Component Analysis (PCA) was chosen as the factor extraction method. The PCA was chosen to uncover latent dimensions without imposing a predefined factor structure. To enhance the interpretability of factors, a varimax rotation was applied. Varimax is an orthogonal rotation method that simplifies factor loadings by maximizing the variance of loadings on each factor (Kaiser, 1958). The analysis was performed, and 11 components were initially extracted explaining 43.4% of the total variance extracted. However, a total of 25 items were screened for cross-loading unto multiple components, loading solitarily unto components, not loading unto a component in the matrix, and having loadings below the recommended threshold of .04 (Owan et al., 2021).

Table 1: Results summary of the total variance explained by the extracted components in the PIRC scale

	Initial Eigenvalues			Extraction Sums of Squared Loadings			Rotation Sums of Squared Loadings		
Components	Total	% of S^2	Cum. %	Total	% of S^2	Cum. %	Total	% of S^2	Cum. %
1	5.71	14.65	14.65	5.71	14.65	14.65	5.17	13.26	13.26
2	5.21	13.36	28.01	5.21	13.36	28.01	5.05	12.95	26.20
3	4.84	12.42	40.43	4.84	12.42	40.43	4.79	12.28	38.48
4	4.56	11.70	52.13	4.56	11.70	52.13	4.65	11.93	50.41
5	3.98	10.22	62.34	3.98	10.22	62.34	4.28	10.98	61.39
6	3.84	9.84	72.19	3.84	9.84	72.19	4.21	10.80	72.19
7	0.95	2.44	74.62						
8	0.94	2.40	77.02						
9	0.85	2.17	79.19						
10	0.81	2.08	81.27						
11	0.63	1.62	82.89						
12	0.59	1.52	84.41						
13	0.50	1.28	85.69						
14	0.42	1.08	86.77						
15	0.40	1.02	87.79						
16	0.37	0.94	88.73						
17	0.35	0.90	89.63						
18	0.31	0.79	90.41						
19	0.30	0.77	91.18						
20	0.28	0.72	91.90						
21	0.26	0.67	92.57						
22	0.25	0.64	93.21						
23	0.24	0.61	93.82						
24	0.23	0.59	94.41						
25	0.22	0.55	94.96						
26	0.20	0.52	95.47						
27	0.19	0.50	95.97						
28	0.18	0.45	96.42						
29	0.17	0.44	96.85						
30	0.16	0.42	97.27						
31	0.16	0.41	97.68						
32	0.14	0.37	98.05						
33	0.14	0.35	98.40						
34	0.13	0.33	98.72						
35	0.12	0.30	99.03						
36	0.10	0.26	99.29						
37	0.10	0.26	99.54						
38	0.09	0.24	99.78						
39	0.08	0.22	100.00						

Extraction Method: Principal Component Analysis.

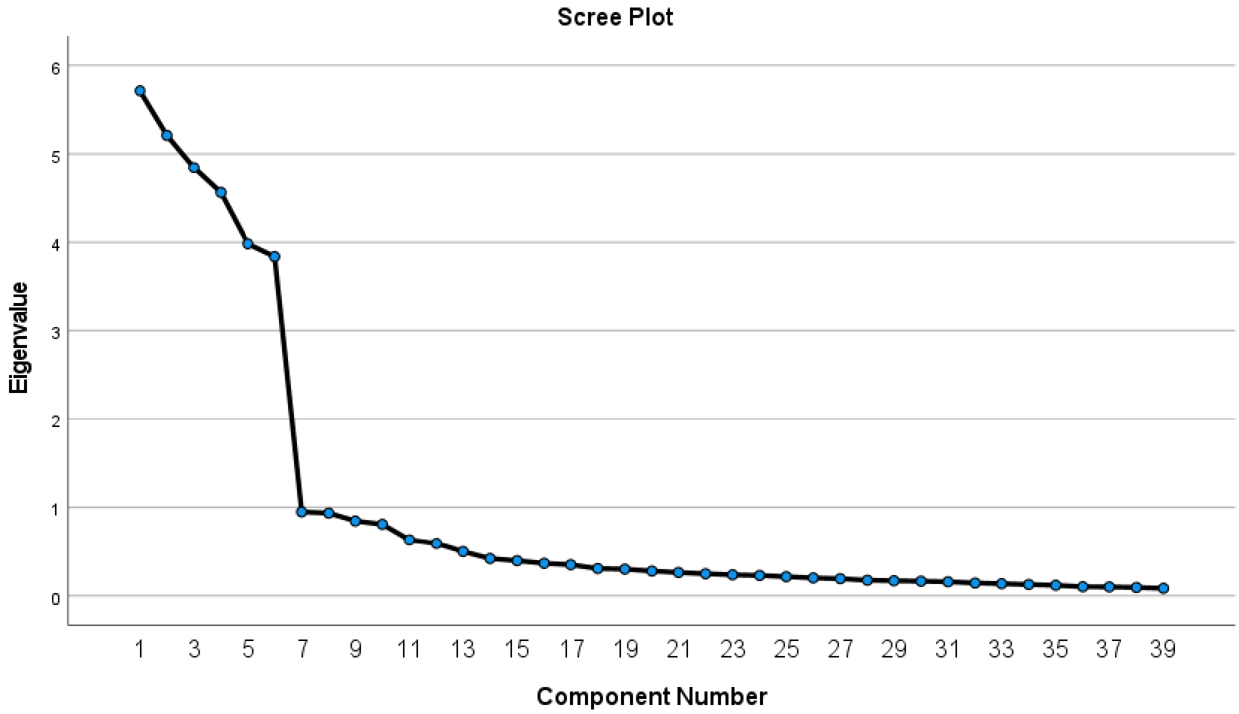

Figure 2: Scree plot of the component structure of the PIRC scale

After eliminating the 25 dysfunctional items, the analysis was re-run with the same settings earlier described. Six components were extracted, which jointly explained 72.19% of the extracted sums of squared loadings. The first component explained 14.65% of the extracted sums of squared loadings. Similarly, the second, third, fourth, fifth and sixth components explained 13.36%, 12.42%, 11.70%, 10.22% and 9.84% of the extracted sums of variance, respectively (See Table 1). The scree plot (Figure 2) also visualises six factors with Eigenvalues above one. For sampling adequacy, a KMO value of .866 was obtained, with a significant Bartlett's test of sphericity, χ^2 = 68158.35, p < .001. This shows that the sample of 1,929 respondents is large enough and suitable for factor analysis.

The rotated component matrix (Table 2) was evaluated for the specific loadings of each item to their corresponding components for the interpretation of each of the six retained factors and naming purposes. The first component, "challenges of IDR collaboration," encapsulated items related to problems IDR teams face during collaboration. The item loadings in this component range from .726 to .896. The second component, "IDR collaborative experiences," represented items reflecting the experiences of researchers engaged in interdisciplinary projects. Item loadings in this component range from .742 to .898. The third component, "motivations for IDR collaboration," included items probing into the motivating factors driving individuals to engage in interdisciplinary research collaboration. The item loadings within this component are in the range of .721 and .927. The fourth component, "benefits of IDR collaboration," represents perceptions of the benefits and advantages of interdisciplinary approaches in the field of research. The items in this component loaded in the range of .665 and .935. The fifth component, "career impact of IDR collaboration," focused on items assessing the influence of interdisciplinary research collaboration on career development. The loading of the items in this component ranges from .616 to .836. The sixth component, "IDR team dynamics", represents positive dynamics and effective functioning of interdisciplinary teams in research. The item loadings within this component are in the range of .768 and .895.

Table 2: Exploratory Factor Analysis for the PIRC scale

Item	Description	λ	Component
ITM1	An unequal number of members creates dominance of some disciplines over others in the team	.896	Challenges of IDR Collaboration
ITM7	Authorship disputes are common when publishing interdisciplinary research.	.886	
ITM8	Pursuing a research agenda that aligns with the interests of all members can be challenging	.883	
ITM22	Misunderstandings in communication are common when collaborating across disciplines.	.883	
ITM21	Conflicting schedules make coordinating meetings with interdisciplinary team members	.881	
ITM31	The lack of experienced leaders affects the success rate of interdisciplinary research teams.	.826	
ITM14	Learning the language of another discipline is a barrier to interdisciplinary collaboration.	.726	
ITM5	Collaborative projects have generally improved the quality of my research.	.898	IDR Collaborative
ITM10	I have been satisfied with the outcomes of most of my collaborative research endeavours.	.892	

ITM23	My collaborative experiences have consistently led to the development of innovative ideas.	.884	
ITM12	I enjoy productivity when collaborating with colleagues from different disciplines.	.878	
ITM9	I have a sense of accomplishment from my past collaborative work.	.877	
ITM13	I have had the opportunity to learn other methodologies from interdisciplinary collaborators.	.748	
ITM3	Collaborating with colleagues from different disciplines has enhanced my skills.	.742	
ITM28	Breaking new ground in my research field motivates me to collaborate across disciplines	.927	Motivations for IDR Collaboration
ITM24	My goal is to expand my expertise when working with colleagues from other fields.	.925	
ITM32	Generating innovative solutions drives my motivation to collaborate outside my field.	.918	
ITM39	There is an experience of excitement while collaboratively tackling challenging problems	.915	
ITM34	I have a sense of accomplishment in addressing key issues through interdisciplinary research	.908	
ITM25	I strongly believe that interdisciplinary research always enhances my research quality.	.721	
ITM29	Integrating various research methods from different disciplines can tackle a complex problem	.935	Benefits of IDR Collaboration
ITM4	Collaborating with scholars from different fields increases exposure to diverse perspectives	.934	
ITM19	Interdisciplinary teams are more likely to receive funding for research projects.	.927	
ITM35	Some problems beyond the scope of a discipline warrant interdisciplinary collaboration.	.887	
ITM18	Interdisciplinary research can lead to discoveries that have a broader societal impact.	.883	
ITM15	Interdisciplinary collaboration fosters connections with scholars from various backgrounds.	.665	
ITM11	Interdisciplinary projects have afforded me increased opportunities for self-development	.836	Career impact of IDR Collaboration
ITM26	My participation in interdisciplinary research projects has enhanced my visibility.	.831	
ITM16	Interdisciplinary collaboration is valuable for my career growth.	.829	
ITM33	The results of interdisciplinary collaborations have enhanced my research citations.	.826	
ITM30	Interdisciplinary collaboration has improved my prospects for securing research grants.	.813	
ITM17	Interdisciplinary collaborations have boosted my reputation beyond my field of research.	.670	
ITM2	Collaborating across disciplines has expanded my professional network.	.616	
ITM20	Interdisciplinary teams I work with often demonstrate a sense of unity.	.895	IDR team dynamics
ITM6	Disagreements are resolved constructively within our interdisciplinary teams.	.880	
ITM36	There are well-defined responsibilities that contribute to the smooth functioning of our teams.	.845	
ITM37	There is mutual respect among team members in my interdisciplinary research teams.	.812	
ITM27	Team members from different disciplines actively learn from one another.	.791	
ITM38	There is a sense of shared commitment to the success of our interdisciplinary projects.	.768	

Notes: Extraction Method: Principal Component Analysis; Rotation Method: Varimax with Kaiser Normalization; Rotation converged in 5 iterations.

Test of Dimensionality

The test of dimensionality was conducted using Confirmatory Factor Analysis (CFA) to validate the factor structure identified by the EFA. This fit of the data to the hypothesised factor structure was assessed to determine whether the instrument measures the intended dimensions of interdisciplinary research collaboration (Owan et al., 2022; Owan et al., 2021; Tripp & Shortlidge, 2020). In this study, four competing CFA models were developed to test the dimensionality of the PIRC scale further. The aim was to determine the model that best captures the relationships between variables and provides the most accurate representation of the data (Ganesh & Srivastava, 2022). Various fit indices were also used to determine which theoretical framework best explained the relationships among latent constructs and observed variables (Owan et al., 2023c).

The first model (Model 1) is the unidimensional or single-factor model (See Figure 3). This model assumes that all the items in the PIRC scale measure a single underlying factor, representing a unidimensional perspective of interdisciplinary research collaboration perception (Rijnsoever & Hessels, 2011). The second (Model 2) is the oblique model, which assumes relationships between different dimensions of IDR collaboration (See Figure 4). The oblique model allows for the possibility of multiple underlying factors correlated with each other (Smith, 1996). The third (Model 3) is the higher-order or second-order model (See Figure 5), which assumes that there are relationships between the six dimensions of the PIRC scale, as well as the overall "perception of interdisciplinary collaboration" (Shek & Yu, 2014). The fourth (Model 4) is the bi-factor model (See Figure 6). The bi-factor model assumes that the observed variables are grouped into specific factors that represent different dimensions or aspects of the construct being measured, and these specific factors are then grouped into a general factor that represents the overall construct (Owan et al., 2023c). In this study, the bi-factor model includes a general factor representing the overall perception of interdisciplinary research collaboration perception and six components corresponding to distinct dimensions.

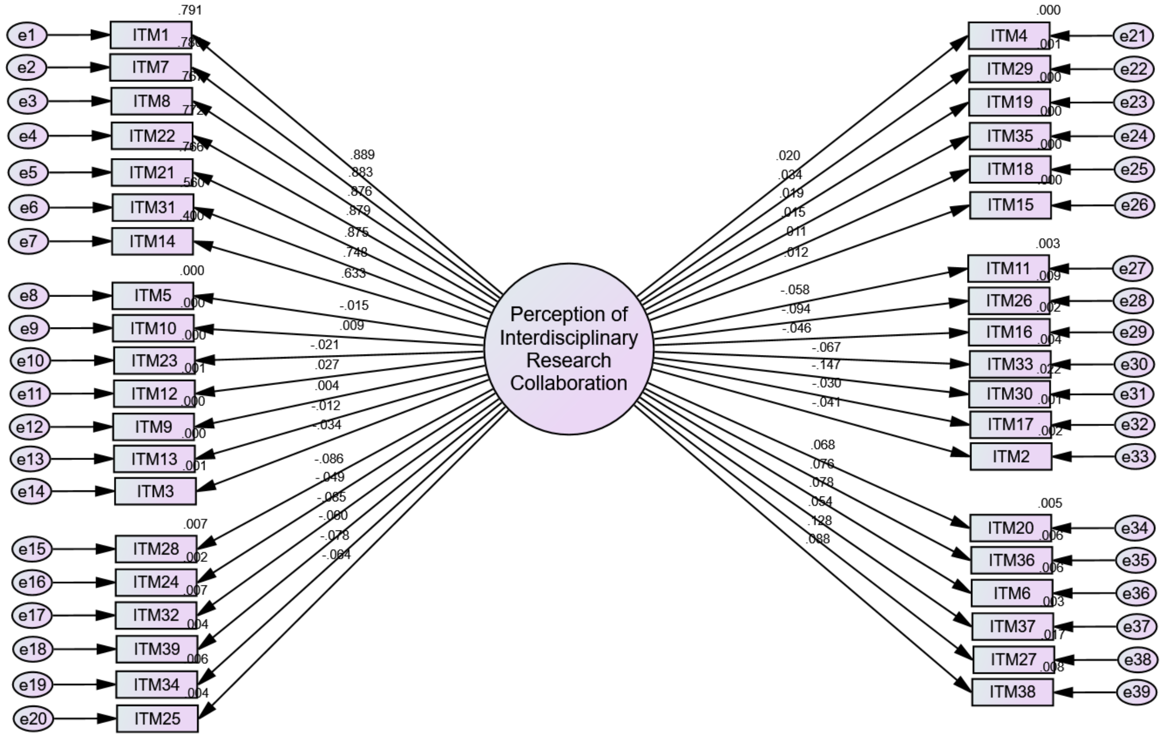

Figure 3: Model 1 – Unidimensional CFA model of the PIRC Scale

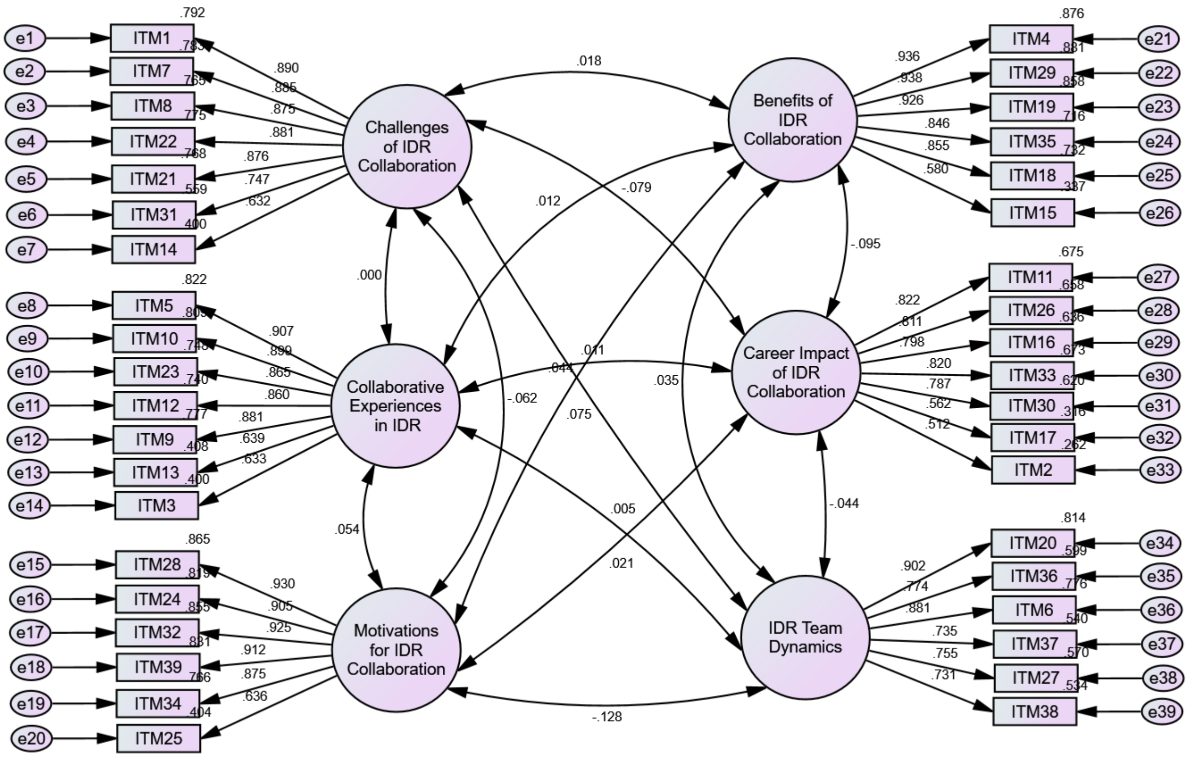

Figure 4: Model 2 – Oblique CFA model of the PIRC Scale.

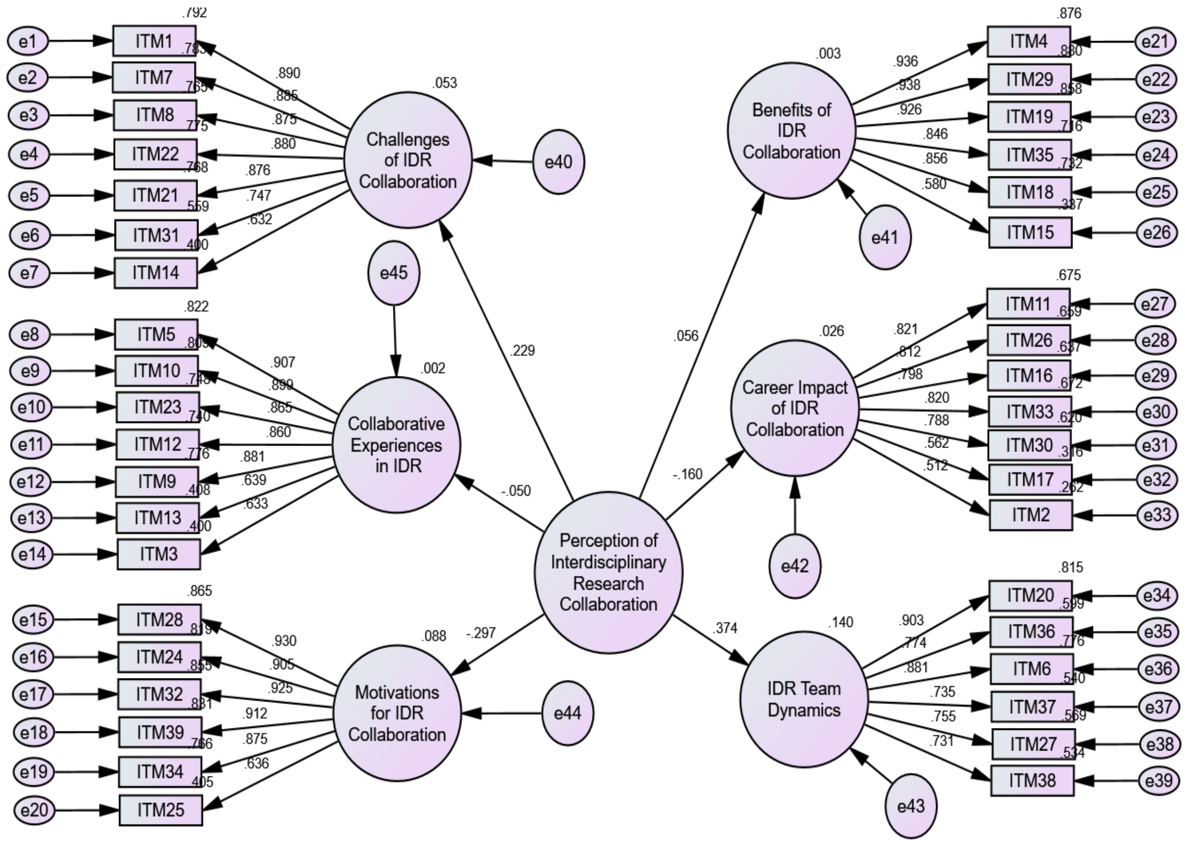

Figure 5: Model 3 – Higher-order CFA model of the PIRC Scale

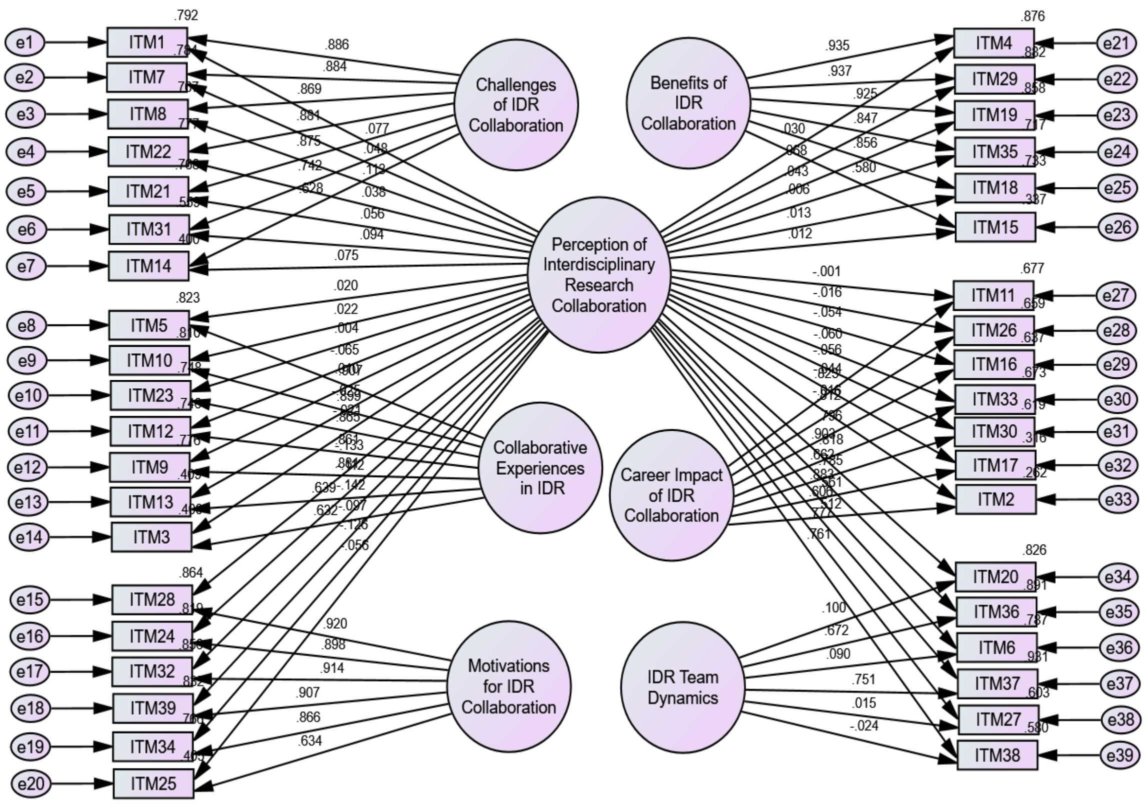

Figure 6: Model 4 – Bi-factor CFA model of the PIRC Scale.

In deciding the model that best fit the data, the four competing models were evaluated using seven fit indices: the Chi-square (χ^2), "Standardised Root Mean Residual (SRMR)," "Tucker-Lewis Index (TLI)," "Comparative Fit Index (CFI)," "Root Mean Square Error of Approximation (RMSEA)," "Akaike's Information Criterion (AIC)" and "Bayesian Information Criterion (BIC)." According to Table 3, all four models did not have an acceptable fit based on the Chi-square criteria since their p-values are all less than the .05 alpha level. The result is understandable since the sample size of 1,929 is very large. The Chi-square test has been proven to be sensitive to sample size, with models exhibiting poor fits in samples larger than 400 participants (Bassey et al., 2019; Ekpenyong et al., 2022). Under the SRMR criteria, the unidimensional model exhibited the poorest fit of the four competing models. The oblique, higher-order and bi-factor models had acceptable fits based on SRMR criteria, with the oblique model having the best fit.

Table 3: Fit indices and model comparison of the four competing CFA models

Fit Index	Cut-off	Model 1	Model 2	Model 3	Model 4
χ^2 (df), p-value	p > .05	57256.42(702), p < .001	9215.78 (687), p < .001	9246.77 (696), p< .001	7030.63 (663), p< .001
SRMR	< .08	.226	.039	.043	.042
TLI	≥ .95	.121	.865	.866	.895
CFI	≥ .95	.167	.874	.874	.906
RMSEA	< .08	.204	.080	.080	.071
AIC	NA	57412.42	9401.78	9414.77	7264.63
BIC	NA	57846.47	9919.30	9882.21	7915.71

Model 1 = Single factor model; Model 2: Oblique model; Model 3: Higher order model; Model 4: Bi-factor model; SRMR = Standardised root mean residual; TLI = Tucker-Lewis Index; NA = Not applicable

For the TLI and CFI, Table 3 shows none of the four models reached the ≥ .95 threshold, although the oblique, higher-order and bi-factor models had values approaching the threshold. However, the unidimensional CFA model had TLI and CFI values closer to zero, making it the worst model in relation to the others. For the RMSEA, none of the models met the <.08 cut-off mark except the bi-factor model. The AIC and BIC also provided evidence that the bi-factor model has the best fit since, compared to others, it has the lowest AIC and BIC. In conclusion, the bi-factor model provided the best fit, followed by the oblique and higher-order models. This suggests that a general factor (perception of interdisciplinary research) influences the observed variables, as well as specific factors that capture unique variance in each variable. The Specific item loadings in the CFA models are provided in Table 4.

Table 4: Loadings of Confirmatory Factor Analysis for the four competing models

Paths for the general factor	Model 1	Model 4	Paths for specific factors	Model 2	Model 3	Model 4
PIRC→ITM1	.889	.077	CIDR→ITM1	.890	.890	.886
PIRC→ITM7	.883	.048	CIDR→ITM7	.885	.885	.884
PIRC→ITM8	.876	.113	CIDR→ITM8	.875	.875	.869
PIRC→ITM22	.879	.038	CIDR→ITM22	.881	.880	.881
PIRC→ITM21	.875	.056	CIDR→ITM21	.876	.876	.875
PIRC→ITM31	.748	.094	CIDR→ITM31	.747	.747	.742
PIRC→ITM14	.633	.075	CIDR→ITM14	.632	.632	.628
PIRC→ITM5	-.015	.020	CEIDR→ITM5	.907	.907	.907
PIRC→ITM10	.009	.022	CEIDR→ITM10	.899	.899	.899
PIRC→ITM23	-.021	.004	CEIDR→ITM23	.865	.865	.865
PIRC→ITM12	.027	-.065	CEIDR→ITM12	.860	.860	.861
PIRC→ITM9	.004	.010	CEIDR→ITM9	.881	.881	.881
PIRC→ITM13	-.012	-.025	CEIDR→ITM13	.639	.639	.639
PIRC→ITM3	-.034	-.021	CEIDR→ITM3	.633	.633	.632
PIRC→ITM28	-.086	-.133	MIDR→ITM28	.930	.930	.920
PIRC→ITM24	-.049	-.112	MIDR→ITM24	.905	.905	.898
PIRC→ITM32	-.085	-.142	MIDR→ITM32	.925	.925	.914
PIRC→ITM39	-.060	-.097	MIDR→ITM39	.912	.912	.907
PIRC→ITM34	-.078	-.126	MIDR→ITM34	.875	.875	.866
PIRC→ITM25	-.064	-.056	MIDR→ITM25	.636	.636	.634
PIRC→ITM4	.020	.030	BIDR→ITM4	.936	.936	.935
PIRC→ITM29	.034	.068	BIDR→ITM29	.938	.938	.937
PIRC→ITM19	.019	.043	BIDR→ITM19	.926	.926	.925
PIRC→ITM35	.015	.006	BIDR→ITM35	.846	.846	.847
PIRC→ITM18	.011	.013	BIDR→ITM18	.855	.856	.856
PIRC→ITM15	.012	.012	BIDR→ITM15	.580	.580	.580
PIRC→ITM11	-.058	-.001	CIIDR→ITM11	.822	.821	.823
PIRC→ITM26	-.094	-.016	CIIDR→ITM26	.811	.812	.812

PIRC→ITM16	-.046	-.054	CIIDR→ITM16	.798	.798	.796
PIRC→ITM33	-.067	-.060	CIIDR→ITM33	.820	.820	.818
PIRC→ITM30	-.147	-.056	CIIDR→ITM30	.787	.788	.785
PIRC→ITM17	-.030	-.044	CIIDR→ITM17	.562	.562	.561
PIRC→ITM2	-.041	-.016	CIIDR→ITM2	.512	.512	.512
PIRC→ITM20	.068	.903	TD→ITM20	.902	.903	.100
PIRC→ITM36	.076	.662	TD→ITM36	.774	.774	.672
PIRC→ITM6	.078	.883	TD→ITM6	.881	.881	.090
PIRC→ITM37	.054	.606	TD→ITM37	.735	.735	.751
PIRC→ITM27	.128	.777	TD→ITM27	.755	.755	.015
PIRC→ITM38	.088	.761	TD→ITM38	.731	.731	-.024

Model 1: Unidimensional or single-factor model; Model 2: Oblique or correlated factor model; Model 3: Higher order or hierarchical model; Model 4: Bifactor model. PIRC = Perception of interdisciplinary research collaboration; CIDR = Challenges of Interdisciplinary Research; CEIDR = Collaborative experiences of interdisciplinary research; MIDR = Motivations for interdisciplinary research; BIDR = Benefits of interdisciplinary research; CIIDR = Career impact of interdisciplinary research; TD = Team dynamics in interdisciplinary research.

Convergent and Discriminant Validity

Convergent validity refers to the correlation between the instrument and a theoretical dimension measure that targets the same aspects of the construct the instrument is designed to measure (Nunes et al., 2023). On the other hand, discriminant validity refers to the instrument's ability to distinguish groups in relation to the underlying construct (Kimberlin & Winterstein, 2008). The Fornell-Larcker approach to convergent and discriminant validity was employed in this study. The Fornell and Larcker approach is widely used for establishing convergent and discriminant validity in the context of covariance-based structural equation modelling (SEM) Henseler et al. (2014). This approach systematically assesses how much a measurement instrument measures the intended construct and distinguishes it from other constructs. To apply the Fornell and Larcker approach, researchers typically calculate the average variance extracted (AVE) for each latent factor (Owan et al., 2022a,b). The AVE represents the amount of variance captured by the indicators of a latent factor relative to the measurement error (Fornell & Larcker, 1981). As shown in Table 5, all the components achieved convergent validity since their Average Variance Extracted is greater than the recommended threshold of 0.50. To assess discriminant validity using the Fornell-Larcker criterion, the square roots of the AVE for each construct (bolded diagonal elements) were compared with the correlations between constructs (off-diagonal elements). As seen in Table 5, the square root of the AVE for each construct (the bolded values) in the leading diagonal are all greater than the correlation between each construct and other constructs.

Table 5: Convergent and discriminant validity evidence of the PIRC Scale

Components	CR	AVE	1	2	3	4	5	6
1. Challenges of IDR Collaboration	.950	.733	**.856**					
2. IDR Collaborative Experiences	.947	.719	.000	**.848**				
3. Motivations for IDR collaboration	.957	.719	-.058	.058	**.848**			
4. Benefits of IDR Collaboration	.957	.790	.016	.013	.040	**.889**		
5. Career impact of IDR collaboration	.914	.769	-.075	.010	.016	-.085	**.877**	
6. IDR collaboration team dynamics	.931	.694	.079	.006	-.112	.025	-.040	**.833**

CR = Composite reliability – Values should be greater than .70
AVE = Average Variance Extracted – Values should be greater than .50
Bolded values along the leading diagonal are square roots of the AVE for discriminant validity.

Test of Reliability

The instrument's reliability was assessed to ensure that the PIRC scale consistently measures the perception of interdisciplinary research collaboration. This was done by calculating the degree of internal consistency using measures such as Cronbach's alpha (α), McDonald's omega (ω), and split-half reliability corrected with Spearman Brown's prophecy formula (rtt). The result of the analysis is presented in Table 6. Reliability estimates were computed for all the sub-scales and the overall instrument.

Table 6: Reliability estimates based on measures of internal consistency.

S/N	Components	M	S^2	SD	k	ω	α	rtt
1	Challenges of IDR collaboration	17.61	42.25	6.50	7	.938	.939	.895
2	IDR collaborative experiences	24.93	10.40	10.20	7	.932	.934	.891
3	Motivations for IDR collaboration	18.18	54.92	7.41	6	.948	.946	.939
4	Benefits of IDR collaboration	21.56	78.86	8.88	6	.942	.938	.929
5	Career impact of IDR collaboration	17.24	35.79	5.98	7	.89	.891	.833
6	Team dynamics in IDR collaboration	17.34	49.28	7.02	6	.909	.913	.936
	Overall PIRC Scale	116.86	361.65	19.02	39	.668	.805	–

M = Mean; S2 = Variance; SD = Standard deviation; k = Number of items; ω = McDonald's omega; α = Cronbach's alpha; rtt = Split-half reliability coefficient corrected with Spearman Brown prophecy formula

According to Table 6, the reliability estimates for each sub-scale across the three measures were above .70, indicating that items within each sub-scale are acceptable. The overall reliability of the PIRC scale is .805 for Cronbach's alpha and .668 for McDonald's omega. For Cronbach's alpha, this indicates that the items within the PIRC scale, when taken together, show good internal consistency in measuring the same underlying construct. The McDonald's omega value is slightly lower than expected, indicating some variability in the scale's internal consistency. This suggests there may be some heterogeneity in the items, and the scale may not be as internally consistent as one would ideally want.

Table 7: Assessment of the quality, impact, and reliability of individual items within each sub-scale

Components	Items	M	SD	Scale M if Item deleted	Scale S^2 if item deleted	Corrected item-total r	Squared multiple r	α if Item deleted	ω if Item deleted
Challenges of IDR Collaboration	ITM1	2.52	1.08	15.09	30.89	.851	.750	.925	.922
	ITM7	2.50	1.09	15.10	30.94	.832	.747	.927	.924
	ITM8	2.55	1.11	15.06	30.73	.835	.724	.927	.923
	ITM22	2.56	1.07	15.05	31.16	.830	.738	.927	.924
	ITM21	2.50	1.07	15.11	31.23	.828	.743	.927	.924
	ITM31	2.48	1.08	15.13	31.60	.777	.771	.932	.935
	ITM14	2.49	1.09	15.12	32.92	.654	.699	.943	.944
IDR Collaborative experiences	ITM5	3.54	1.68	21.39	76.38	.843	.790	.919	.914
	ITM10	3.59	1.69	21.34	76.37	.838	.777	.919	.915
	ITM23	3.58	1.76	21.35	75.46	.830	.716	.920	.915
	ITM12	3.68	1.74	21.25	76.02	.823	.715	.920	.916
	ITM9	3.57	1.73	21.36	76.30	.820	.745	.921	.916
	ITM13	3.48	1.71	21.46	80.21	.682	.695	.933	.936
	ITM3	3.49	1.74	21.44	80.00	.675	.688	.934	.937
Motivations for IDR Collaboration	ITM28	3.05	1.40	15.13	37.69	.889	.824	.930	.931
	ITM24	3.04	1.40	15.14	37.77	.887	.801	.930	.933
	ITM32	3.00	1.39	15.18	38.00	.878	.825	.931	.933
	ITM39	3.06	1.37	15.12	38.38	.867	.800	.933	.934
	ITM34	3.01	1.39	15.16	38.09	.871	.770	.932	.936
	ITM25	3.02	1.41	15.16	41.37	.636	.524	.959	.960
Benefits of IDR Collaboration	ITM4	3.68	1.67	17.89	54.14	.894	.843	.917	.922
	ITM29	3.58	1.69	17.98	53.67	.899	.846	.916	.921
	ITM19	3.60	1.71	17.97	53.77	.884	.824	.918	.923
	ITM35	3.58	1.67	17.99	55.41	.833	.704	.925	.931
	ITM18	3.51	1.75	18.06	54.62	.821	.712	.926	.931
	ITM15	3.62	1.68	17.94	61.02	.574	.365	.955	.956
Career impact of IDR collaboration	ITM11	2.48	1.10	14.76	26.11	.753	.640	.866	.864
	ITM26	2.47	1.09	14.77	26.25	.746	.605	.867	.864
	ITM16	2.47	1.08	14.77	26.36	.745	.574	.868	.865
	ITM33	2.45	1.13	14.79	26.00	.740	.638	.868	.865
	ITM30	2.49	1.11	14.75	26.28	.726	.584	.870	.867
	ITM17	2.43	1.11	14.81	27.84	.577	.434	.888	.892
	ITM2	2.46	1.08	14.78	28.57	.524	.408	.893	.896
Team dynamics in IDR collaboration	ITM20	2.85	1.41	14.49	33.62	.840	.742	.885	.876
	ITM36	2.93	1.41	14.40	34.51	.771	.841	.895	.898
	ITM6	2.89	1.41	14.45	33.86	.818	.715	.888	.880
	ITM37	2.93	1.42	14.41	35.12	.724	.823	.902	.904
	ITM27	2.81	1.39	14.52	35.62	.706	.548	.904	.898
	ITM38	2.93	1.37	14.41	36.21	.677	.528	.908	.902

M = Mean; SD = Standard deviation; S^2 = Variance; r = correlation; α = Cronbach alpha; ω = McDonald's omega

Furthermore, item-total correlation analyses were performed for each item within the instrument to examine the relationship between individual items and their respective factors (see Table 7). All items demonstrated high positive correlations with their assigned factors, reinforcing the instrument's internal consistency and the alignment of items with their intended dimensions. Specifically, the results in Table 7 showed that none of the items significantly affected the reliability of all the sub-scales if deleted. Consequently, no revisions were considered necessary to the items in the scale.

Scoring and Interpretation Guidelines

The PIRC instrument assesses individuals' perceptions of interdisciplinary research collaboration. The scoring guidelines are presented in Table 8. Table 8 reveals that each item in the instrument is scored on a four-point Likert scale, ranging from 1 (Strongly Disagree) to 4 (Strongly Agree). Participants' responses to individual items are summed to calculate their overall score. For each item, assign the following scores: Strongly Disagree: 1 point; Disagree: 2 points; Agree: 3 points; Strongly Agree: 4 points. This scoring system aligns with many previous studies (e.g., Alabi & Jelili, 2023; Ekpenyong et al., 2022, 2023; Owan et al., 2023c). Sum the scores for all items to obtain the participant's total score on the PIRC instrument. The total score for each dimension in the questionnaire will vary depending on the number of items in the dimension. For the overall PIRC scale, a minimum score of 39 and a maximum score of 156 can be obtained. The interpretation of the PIRC scores is as follows:

Table 8: Scoring guidelines for the PIRC scale

S/N	Components	No. of items	Score range	Interpretation cut-off
1	Challenges of IDR collaboration	7	7 to 28	7 to 14 = low; 15 to 22 = moderate; Above 22 = high
2	IDR collaborative experiences	7	7 to 28	7 to 14 = low; 15 to 22 = moderate; Above 22 = high
3	Motivations for IDR collaboration	6	6 to 24	6 to 12 = low; 13 to 19 = moderate; Above 19 = high
4	Benefits of IDR collaboration	6	6 to 24	6 to 12 = low; 13 to 19 = moderate; Above 19 = high
5	Career impact of IDR collaboration	7	7 to 28	7 to 14 = low; 15 to 22 = moderate; Above 22 = high
6	Team dynamics in IDR collaboration	6	6 to 24	6 to 12 = low; 13 to 19 = moderate; Above 19 = high
	Overall PIRC Scale	39	39 to 156	39 to 78 = low; 79 to 118 = moderate; Above 118 = high; Above 118 = high

DISCUSSION

The present study developed and validated the Perception of Interdisciplinary Research Collaboration (PIRC) Scale. This self-report questionnaire measures researchers' perceptions of interdisciplinary research collaboration. The study followed a rigorous methodology, including content validity procedures, pretesting of items, pilot testing, factor analysis, and assessments of dimensionality, reliability, and validity. The findings of this study have significant implications for understanding and assessing perceptions of interdisciplinary research collaboration among researchers and scholars. The factor analysis revealed a six-factor structure of the PIRC Scale. These factors represent distinct dimensions of researchers' perceptions of interdisciplinary research collaboration. The identified dimensions include challenges of IDR collaboration, IDR collaborative experiences, motivations for IDR collaboration, benefits of IDR collaboration, career impact of IDR collaboration, and IDR team dynamics. This multifaceted structure underscores the complexity of interdisciplinary research collaboration and highlights the various factors contributing to researchers' perceptions in this context.

The study employed confirmatory factor analysis (CFA) to validate the factor structure. Four competing models, including unidimensional, oblique, higher-order, and bi-factor models, were tested to determine the best-fitting model. This approach aligns with the one adopted by other studies. For instance, Hankins (2008) discusses the factor structure of the twelve-item General Health Questionnaire (GHQ-12) and compares competing models using confirmatory factor analysis. In the present study, the bi-factor model demonstrated the best fit, providing evidence that a general factor underlying perceptions of interdisciplinary research collaboration influences individual dimensions. The corroborates the research of Owan et al. (2023c) that the bi-factor model was the best fitting of the four models compared. The finding further supports the idea that a general factor underlying perceptions of interdisciplinary research collaboration enables effective collaboration and knowledge integration (Lee et al., 2009).

One potential application of the bi-factor model is in educational research. For example, a study by Chen et al. (2019) used the bi-factor model to examine the factor structure of a questionnaire measuring students' academic self-concept. The results indicated that a general factor of academic self-concept influenced specific factors such as math, reading, and science. The bi-factor model has been used in psychology to explore the factor structure of various constructs. For instance, Reise et al. (2012) applied the bi-factor model to investigate the factor structure of the Inventory of Depression and Anxiety Symptoms (IDAS). The results revealed a general factor of emotional distress that influenced specific factors related to depression and anxiety symptoms. In the present study, the oblique model also showed acceptable fit indices, reinforcing that the dimensions are related but distinct. These findings underscore the multidimensional nature of perceptions related to interdisciplinary research collaboration.

The present study further assessed the convergent and discriminant validity of the PIRC scale following the Fornell-Larcker approach. The results showed that all components achieved convergent validity, with average variance extracted (AVE) values exceeding the recommended threshold of 0.50. Like the results of this study, some researchers also utilised the AVE and the Fornell-Larcker criterion to examine the discriminant validity of a scale (Hayat et al., 2023). Discriminant validity was supported, as the square roots of the AVE for each construct were greater than the correlations between constructs. These findings align with the results of other studies (Owan et al., 2023c), indicating that the PIRC Scale effectively measures the intended construct and can distinguish it from other related constructs.
In the present study, reliability analyses demonstrated the internal consistency of the PIRC Scale. Cronbach's alpha and McDonald's omega values for each sub-scale were consistently above 0.70, indicating good internal consistency. While the overall McDonald's omega value was slightly lower than expected, suggesting some variability in item consistency, it still indicated an acceptable level of reliability. Item-total correlation analyses further confirmed the instrument's internal consistency, as no items significantly affected the reliability of the sub-scales when deleted. This result aligns with those obtained by Owan et al. (2023c) for the persistence of publishing the questionnaires.

The development and validation of the PIRC Scale offer several practical implications. First, it provides researchers, academics, and scholars with a reliable and valid tool to assess perceptions of interdisciplinary research collaboration. This instrument can be valuable in research and educational settings, enabling researchers to measure and understand the attitudes, beliefs, and experiences of individuals engaged in interdisciplinary research. Second, identifying multiple dimensions within the PIRC Scale underscores the complexity of interdisciplinary research collaboration. Researchers and institutions can use this instrument to gain insights into specific areas where improvements may be needed, whether in addressing challenges, enhancing collaborative experiences, or recognising interdisciplinary work's benefits and career impacts.

Limitations and Future Directions

Despite its strengths, this study has some limitations. The sample used for validation was drawn from universities in South-South Nigeria, which may limit the generalizability of the findings to other cultural and geographical contexts. Future research should aim to validate the PIRC Scale in diverse settings to enhance its applicability. Additionally, while the PIRC Scale provides valuable insights into perceptions of interdisciplinary research collaboration, it does not capture interdisciplinary research teams' actual behaviours and outcomes. Future studies could explore the relationship between perceptions and actual interdisciplinary collaboration outcomes to understand the field better. Therefore, the predictive validity of the PIRC scale should be evaluated using other outcomes such as research productivity, research impact, research funding acquisition, team formation, cross-disciplinary publications, innovation and creativity, and career advancement, among others.

CONCLUSION

The development and validation of the PIRC Scale have contributed considerably to the interdisciplinary research field. The scale's comprehensive nature, established through concept analysis, expert input, and extensive pilot testing, ensures its accuracy in evaluating researchers' perceptions across six distinct dimensions. The demonstrated reliability and validity confirm the scale's robustness. The PIRC Scale offers a useful tool for measuring the complex aspects of interdisciplinary collaboration, empowering stakeholders such as researchers, institutions, and policymakers to make data-driven decisions that improve collaboration, resource allocation, and innovation. As interdisciplinary research gains prominence in addressing global challenges, the PIRC Scale is well-positioned to foster a deeper understanding of researchers' perspectives, ultimately contributing to advancing collaborative efforts and achieving meaningful outcomes. Future research examining the PIRC Scale's predictive validity in relation to tangible outcomes will further establish its utility and significance in the evolving landscape of interdisciplinary research.

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