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HUMAN–ROBOT COLLABORATION: STUDENTS’ RISK PERCEPTION AND ADAPTATION

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Abstract - Human–robot collaboration is becoming increasingly prevalent in industrial environments, raising important questions about how future engineers perceive and adapt to working alongside collaborative robots. While technical safety measures are well studied, less attention has been given to the psychological and organizational factors that shape readiness for such interaction, particularly among students who will soon enter the workforce. This study investigates how robotics students perceive risk, trust robotic systems, and express their intention to adapt to collaborative work scenarios. The main objective is to understand the relationships between perceived risk, trust in the robot, expected organizational support, and confidence in learning, and how these factors influence adaptation intentions. A structured survey-based methodology was employed, using a scenario-driven questionnaire administered to students enrolled in a robotics program. The collected data were analyzed using standard statistical techniques to evaluate internal consistency, relationships between variables, and predictive models of adaptation intention. The findings indicate that students generally show a positive attitude toward human–robot collaboration, with strong expectations regarding safety support and a willingness to adapt. Trust in the robot, confidence in personal learning ability, and expectations of organizational support emerge as key factors associated with adaptation. Perceived risk does not act solely as a barrier, suggesting that awareness of risk can coexist with readiness to engage in collaborative environments. These results are relevant for universities, educators, and industry stakeholders, as they highlight the importance of integrating not only technical training but also trust-building, safety communication, and confidence development into engineering education to better prepare future professionals for collaborative robotic systems.

Keywords: Human–robot collaboration, Cobots, Robotics students, Risk perception, Trust in robots, Safety climate, Adaptation intention, Automation, Engineering education.

1. Introduction

Collaborative robots (cobots) are now used in many industrial settings. In these settings, people and robots may work in the same area and share tasks. This can help productivity, but it also brings new safety questions and new worries for people. Many recent papers show that safety in human–robot collaboration is not only about hardware. It is also about how the whole system is planned, how tasks are set, and how people are trained and supported [1–7].

A key topic is how safe people feel. A company may follow safety rules and still face problems if workers do not feel ready. One paper proposes checking “safety readiness” before a cobot is introduced, so the organization can see if it is prepared (rules, training, awareness, and routines) [2]. Recent reviews also describe many safety approaches for close human–robot work, including how to think about contact risks and how to reduce them [4–7]. Other studies also show how functional safety design can be linked to risk thinking in a clear framework for HRC applications [3].

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Another key topic is trust. Trust helps people decide when to rely on a robot and when to stay careful. A recent review explains that "trust" is not one simple thing. It depends on the person, the robot, and the context [8]. This matters in practice. If trust is too low, people may avoid the robot and feel stress. If trust is too high, they may become careless. Studies also show that trust can change with task complexity and with how the robot behaves during cooperation [9]. In manufacturing, some work links trust to how communication is organized in human–robot systems [10]. Other work also tries to simplify how we think about trust in robots, so it is easier to measure and compare across settings [11].

At the same time, engineering research shows how close technology is getting to the human side. Several recent works explore brain–computer interface (BCI) systems that translate brain signals into text and improve word prediction in English and Romanian [12]. Other studies show BCI ideas used in assistive systems, such as lower-limb prosthetics [13] and bionic leg prosthesis behavior [14]. BCI is also used for real-time control in home automation [15,16]. These studies are not about factory cobots directly, but they show a clear direction: systems increasingly connect with human signals, human decisions, and human comfort [12–16].

Robotics research also moves toward more natural ways to control robots. Vision-based hand tracking can be used to teleoperate a robotic arm, which can make control feel more direct and more human-friendly [15,16]. Motion quality can also affect comfort. For industrial robots, trajectory smoothness (for example geometric continuity) can change speed and vibration patterns, which can influence how the motion "feels" to a person who works nearby [17]. These technical details can shape people's trust and perceived risk, even if people do not describe them in engineering terms [16,17].

Modern automation also depends on data and software tools. In production, computer vision can help detect defects and support quality control, such as detecting imperfections linked to 3D printing settings [18]. In research and decision making, the way we build models also matters. A study comparing interpolation and extrapolation methods shows that prediction results can change depending on the method and the data range [19]. Other decision tools rank options in complex problems, such as ranking photovoltaic waste recovery options with multi-criteria methods [20]. Software systems also support digital infrastructure and user access, such as monitoring network traffic and enabling access to region-locked services [21]. Mechanical testing and validation remain important too, because many automated systems depend on reliable materials and structures [22]. Together, these examples show a wide pattern: automation is not only about robots. It is also about data, software, decisions, and engineering validation [18–23], [39-43].

Education is part of this same digital shift. Some work proposes inclusive learning platforms that use gesture recognition and local AI models, designed to work offline and support different learners [24,25]. Other papers discuss learning personalization through software tools [26] and using machine learning to predict student performance and help educational decisions [27]. Trust appears in education too. One study shows that students' willingness to allow educational data use depends strongly on trust and governance [28]. So, "trust" is not only a robot topic. It is also a student and learning topic [27,28].

Recent work also looks directly at students' digital life and well-being. One study explores digital engagement and psychological well-being among technical university students [29]. Other papers discuss how AI tools can influence students' academic development and learning practices [30,31]. Because AI use is growing fast, some authors also argue that ethics and safe use should be part of technical training, using practical modules and simple learning designs [15,32]. Other student-focused topics also matter, such as inclusive attitudes [33], habits that can harm long-term learning and sustainability (like perfectionism and workaholism) [34], time management in the technology era [35,36], and learning lessons about data protection after the pandemic [15,37,38]. Together, these studies show that students already live in a world where technology, trust, and well-being are connected [29–38].

This leads to a simple gap. Many HRC studies focus on employees, factory pilots, or lab tasks with sensors. But robotics students will soon design systems, manage projects, and work near cobots. Their beliefs matter because they can shape future practice. If students expect clear rules and good training, they may feel more ready. If they feel high risk and low trust, they may resist or feel stress. For this reason, it helps to study students in a simple way, with low cost and no special equipment.

In this article, we add value in three ways. First, we focus on robotics students who are not employed, so we capture expectations before real workplace exposure. Second, we study both psychological factors (trust in the robot, confidence to learn) and organizational factors (expected procedures, training, and management focus on safety) [2,8,27–30]. Third, we explore how perceived risk, trust, expected safety support, and confidence to learn are linked to adaptation intention. This student-focused view can help universities and future employers plan better training and communication before students become workers and decision makers.

2. Survey Design and Measures

This section explains how we collected the data and how we prepared it for the JASP v0.19.3 analyses described in the Abstract. It is written to be easy to follow and easy to repeat.

2.1. Study Design

We used a short, anonymous online survey. The survey asked students to imagine a simple human–robot collaboration (HRC) situation with a collaborative robot. The scenario was the same for all participants.

All questions were set as Required, so the dataset has no missing answers.

2.2. Participants

The survey was shared with students from the FIIR Robotics program (Year 3 and Year 4).

We received 105 submissions. Four respondents selected 'No' for the FIIR Robotics program question, so we excluded these cases. The final sample was N = 101.

Employment status was also recorded, because we wanted to understand if students already had work exposure (72 out of 101 reported they were not employed). Basic sample characteristics are reported in Table 6.

Because this is a student survey, the results reflect expectations and beliefs, not real factory experience.

2.3. Questionnaire Structure

The questionnaire had 19 questions in total:

- 6 background questions: program, year of study, employment status, gender, age group, and prior exposure to robots (lab/demo/course project).
- 1 short scenario text about working near a cobot in an industrial cell.
- 12 main items grouped into four short scales (3 items each).
- 1 extra item about general confidence to learn to work with a cobot.

All scale items used a 7-point agreement scale (1 = strongly disagree to 7 = strongly agree).

2.4. Measures and Scoring

We used four main constructs and one control item:

- TRUST (Trust in the robot): 3 items (predictable behavior, safe task performance, easy to anticipate).
- ORG (Expected safety support): 3 items (clear procedures, adequate training, management puts safety over speed).
- RISK (Perceived risk): 3 items (risk of accidents, worry about unexpected moves, feeling threatened).
- ADAPT (Adaptation intention): 3 items (willingness to work regularly, ability to adapt, acceptance of workflow changes).
- SELFCONF (Confidence to learn): 1 item (overall confidence to learn to work effectively with a cobot).

For TRUST, ORG, RISK, and ADAPT we computed a mean score (average of the 3 items). Higher scores mean "more" of that concept. No items were reverse-coded.

2.5. Data Preparation and Analysis Plan (JASP)

Responses were exported from Google Forms as a CSV file. Because all questions were required, we did not need missing-data imputation. We treated the 1–7 scale as numeric for analysis.

We used the following analyses in JASP:

- Reliability (Cronbach's alpha and McDonald's omega) for TRUST, ORG, RISK, ADAPT
- Correlations between TRUST, ORG, RISK, ADAPT, and SELFCONF.
- One regression model predicting ADAPT (TRUST, ORG, RISK, SELFCONF).
- Group differences by employment status (Welch's t-test).
- Hierarchical regression (R^2 change) to show what each block adds.

The next section reports these JASP results in a clear way, with a small number of tables.

3. Results

3.1. Internal Consistency (Cronbach's alpha and McDonald's omega)

We checked the internal consistency of the four multi-item scales (3 items each): TRUST, ORG, RISK, and ADAPT. We report Cronbach's alpha (α) and McDonald's omega (ω), with 95% confidence intervals.

Overall, the scales showed acceptable internal consistency (see Table 1). TRUST had α = 0.757 and ω = 0.764. ORG had α = 0.769 and ω = 0.795. RISK showed the highest reliability (α = 0.822; ω = 0.825). ADAPT had α = 0.741 and ω = 0.765. Item-rest correlations were moderate to high for all items, which suggests that each item fits well with its scale.

Table 1. Internal consistency of the study scales (N = 101)

Scale	**Items**	**α (Cronbach)**	**95% CI for α**	**ω (McDonald)**	**95% CI for ω**
TRUST	3	0.757	[0.649, 0.864]	0.764	[0.684, 0.843]
ORG	3	0.769	[0.659, 0.880]	0.795	[0.728, 0.861]
RISK	3	0.822	[0.751, 0.892]	0.825	[0.767, 0.884]
ADAPT	3	0.741	[0.596, 0.886]	0.765	[0.684, 0.846]

Note: Note. α = Cronbach's alpha; ω = McDonald's omega.

Table 1 shows that all four scales are consistent. This means the three items in each scale "go together" well. RISK has the highest reliability (α = 0.822; ω = 0.825), so students answered those risk items in a very stable way. TRUST and ORG are also strong (α around 0.76–0.77). ADAPT is acceptable (α = 0.741), which is normal for short 3-item scales. Overall, these results support using the mean scores for the next analyses.

We also present a simple visual summary of scale reliability. Figure 1 shows Cronbach's alpha values for the four study scales.

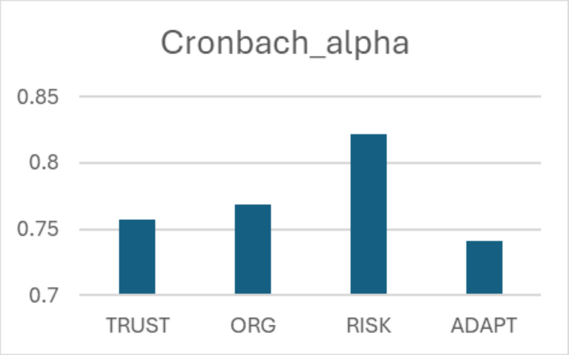

Figure 1: Cronbach's alpha values for the study scales (N = 101)

3.2. Correlations Between Study Variables

We examined Pearson correlations between the main scale scores (TRUST, ORG, RISK, ADAPT) and the control item SELFCONF. The results are shown in Table 2.

TRUST was strongly and positively related to ORG (r = 0.535, p < .001).

TRUST was also positively related to ADAPT (r = 0.492, p < .001) and to SELFCONF (r = 0.377, p < .001). ORG had a positive correlation with ADAPT (r = 0.527, p < .001) and with SELFCONF (r = 0.478, p < .001). RISK showed small negative correlations with TRUST and SELFCONF, but these were not statistically significant (p = .061 and p = .104). RISK was not related to ADAPT (r = 0.084, p = .404).

Table 2. Pearson correlation matrix (N = 101)

Variable	**TRUST**	**ORG**	**RISK**	**ADAPT**	**SELFCONF**
TRUST	—				
ORG	0.535***	—			
RISK	-0.187	-0.048	—		
ADAPT	0.492***	0.527***	0.084	—	
SELFCONF	0.377***	0.478***	-0.163	0.517***	—

*Note: Pearson's r values are shown. *** p < .001*

Table 2 shows a clear pattern. Students who trust the robot more also expect stronger safety support from the organization (TRUST–ORG r = 0.535). Students also report higher adaptation intention when they have higher TRUST (r = 0.492), higher ORG (r = 0.527), and higher SELFCONF (r = 0.517). In simple words, readiness to work with a cobot is linked more to trust, support, and confidence than to fear. RISK has almost no relation with ADAPT in the simple correlation (r = 0.084). This means risk feelings alone do not explain willingness to adapt when we look at only one link at a time.

To make the correlation results easier to read, we also show the main correlations with ADAPT in a simple chart. Figure 2 summarizes how TRUST, ORG, RISK, and SELFCONF relate to adaptation intention.

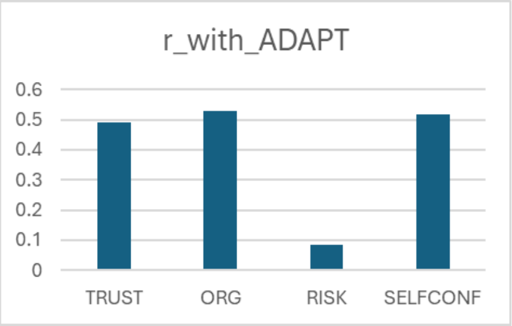

Figure 2: Pearson correlations with adaptation intention (ADAPT) (N = 101)

3.3. Regression Model Predicting Adaptation Intention (ADAPT)

We ran one linear regression model to predict adaptation intention (ADAPT) using TRUST, ORG, RISK, and SELFCONF as predictors (see Table 3). The model was statistically significant (F(4, 96) = 19.525, p < .001) and explained 44.9% of the variance in ADAPT ($R^2 = 0.449$; Adjusted $R^2 = 0.426$).

All four predictors had positive effects in the model. Higher TRUST was linked to higher ADAPT (β = 0.283, p = .003). Higher expected safety support (ORG) was also linked to higher ADAPT (β = 0.225, p = .022). Perceived risk (RISK) showed a small positive effect (β = 0.202, p = .011). SELFCONF had the strongest effect (β = 0.336, p < .001).

Collinearity was not a concern: VIF values were low (1.059–1.619).

Table 3. Linear regression predicting adaptation intention (ADAPT) (N = 101)

Predictor	**B**	**SE**	**β**	**t**	**p**	**VIF**
TRUST	0.252	0.082	0.283	3.066	0.003	1.483
ORG	0.208	0.089	0.225	2.335	0.022	1.619
RISK	0.134	0.052	0.202	2.593	0.011	1.059
SELFCONF	0.334	0.088	0.336	3.806	< 0.001	1.355

Note: B = unstandardized coefficient; SE = standard error; β = standardized coefficient; VIF = variance inflation factor

For model fit it was obtained: $R^2 = 0.449$; Adjusted $R^2 = 0.426$; RMSE = 0.847; F(4,96) = 19.525, p < .001.

Table 3 shows the combined picture, when all predictors are considered at the same time. The model explains about 45% of the differences in ADAPT ($R^2 = 0.449$). SELFCONF is the strongest predictor (β = 0.336), followed by TRUST (β = 0.283) and ORG (β = 0.225). This means confidence to learn, trust, and expected safety support are key drivers of adaptation intention. RISK becomes a small positive predictor in the regression (β = 0.202), even though it was not related to ADAPT in Table 2.

This can happen when other variables (TRUST, ORG, SELFCONF) are controlled. It suggests that "risk awareness" may coexist with readiness, rather than reducing it.

To show the regression results in a simple way, we also plotted the standardized coefficients. Figure 3 shows which predictors have the strongest links with ADAPT when all predictors are considered together.

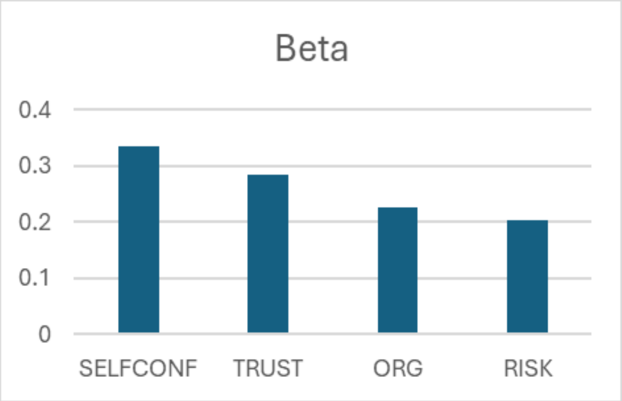

Figure 3: Standardized regression coefficients (β) predicting ADAPT (N = 101)

3.4. Group Differences by Employment Status (Independent Samples t-test)

We compared students who reported being employed (Yes) versus not employed (No) on the main study variables. Because group sizes differ (No = 72; Yes = 29), we report Welch's t-test results. The results are shown in Table 4.

Students who were not employed reported higher TRUST and higher ADAPT. TRUST was higher in the non-employed group (Welch t = 2.235, p = 0.030, d = 0.495). ADAPT was also higher in the non-employed group (Welch t = 3.194, p = 0.003, d = 0.754).

Differences for ORG, RISK, and SELFCONF were not statistically significant (p > 0.05).

Table 4. Group differences by employment status (Welch's t-test)

Variable	**Not employed (n = 72) Mean ± SD**	**Employed (n = 29) Mean ± SD**	**Welch t**	**df**	**p**	**Cohen's d**
TRUST	5.625 ± 1.215	5.011 ± 1.261	2.235	50.092	0.030	0.495
ORG	6.037 ± 1.150	5.839 ± 1.356	0.692	45.086	0.492	0.157
RISK	4.000 ± 1.730	4.379 ± 1.547	-1.077	57.529	0.286	-0.231
ADAPT	5.977 ± 0.918	5.115 ± 1.331	3.194	39.190	0.003	0.754
SELFCONF	6.347 ± 1.023	6.103 ± 1.345	0.879	41.669	0.385	0.204

Note: Welch's t-test is reported due to unequal group sizes. Cohen's d describes effect size (around 0.2 small, 0.5 medium, 0.8 large).

Table 4 suggests that work exposure may change how students think about HRC. Students who already work report lower trust and lower willingness to adapt to cobot work. The difference in TRUST is around a medium effect (d ≈ 0.50), and the difference in ADAPT is medium-to-large (d ≈ 0.75). At the same time, both groups expect similar safety support (ORG), and they report similar confidence to learn (SELFCONF).

This can mean that employed students are not "less capable", but they may be more cautious or more realistic about workplace risks and change.

To make the employment-group differences easier to see, we also show the group means for TRUST and ADAPT in a chart. Figure 4 summarizes the main differences between employed and not employed students.

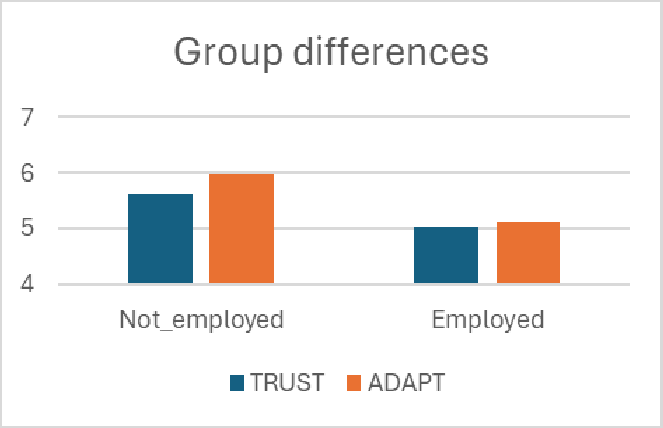

Figure 4: Group differences by employment status for TRUST and ADAPT (N = 101)

3.5. Hierarchical Regression (R^2 change)

We ran a hierarchical regression to see how each block of predictors improves the prediction of adaptation intention (ADAPT). We added the predictors step by step: first TRUST and SELFCONF (Model M_0), then ORG (Model M_1), and finally RISK (Model M_2). The results are shown in Table 5.

Model M0 explained 37.0% of the variance in ADAPT ($R^2 = 0.370$, $p < .001$). When we added ORG in Model M_1, the explained variance increased by 4.0% ($\Delta R^2 = 0.040$, $p = 0.012$). When we added RISK in Model M_2, the explained variance increased by another 3.9% ($\Delta R^2 = 0.039$, $p = 0.011$). The final model (M_2) matched our main regression model and explained 44.9% of ADAPT ($R^2 = 0.449$; Adjusted $R^2 = 0.426$).

Table 5. Hierarchical regression predicting ADAPT (N = 101)

Model	**Predictors added**	**R^2**	**Adjusted R^2**	**RMSE**	**ΔR^2**	**F change (df1, df2)**	**p**
M0	TRUST, SELFCONF	0.370	0.357	0.896	0.370	28.820 (2, 98)	< .001
M1	+ ORG	0.410	0.392	0.871	0.040	6.515 (1, 97)	0.012
M2	+ RISK	0.449	0.426	0.847	0.039	6.725 (1, 96)	0.011

Table 5 shows a simple message. First, most of the prediction comes from personal factors: trust in the robot and confidence to learn already explain about 37% of adaptation intention. Then, expected safety support (ORG) adds a smaller but clear extra part (+4%). This suggests that students' readiness is not only "inside the person". It also depends on what they expect from an organization, like training and clear procedures. Finally, perceived risk (RISK) adds another small part (+4%). This means risk awareness still matters, but it is not the main driver. Overall, the strongest base is trust and confidence, and the other factors refine the picture.

We also present a visual summary of the hierarchical models. Figure 5 shows how the explained variance (R^2) increases from M0 to M2 as new predictors are added.

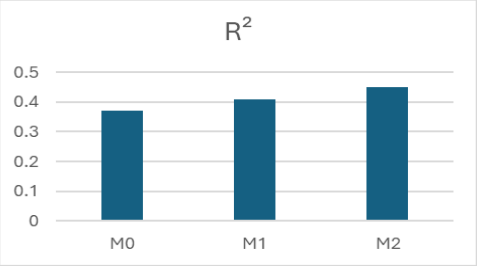

Figure 5: Increase in explained variance (R^2) across the hierarchical regression models (N = 101)

3.6. Sample Characteristics (Descriptive Statistics)

We summarized the background variables using frequency tables. All variables had 101 valid responses and 0 missing values. The sample characteristics are shown in Table 6.

Table 6. Sample characteristics (N = 101)

Variable	**Category**	**n**	**%**
Year of study	Year 3	48	47.5
	Year 4	53	52.5
Employment status	Not employed	72	71.3
	Employed	29	28.7
Gender	Female	21	20.8
	Male	77	76.2
	Prefer not to say	3	3.0
Age group	20–21	39	38.6
	22–23	59	58.4
	24+	3	3.0
Prior robot exposure	Yes	100	99.0
	No	1	1.0

Table 6 shows a balanced split between Year 3 and Year 4 students. Most respondents were not employed, which supports our aim to capture student expectations rather than daily work experience. The sample was mainly male, which is common in many robotics programs. Most students were in the 22–23 age group, which fits the expected age for these study years.

Almost all students reported prior robot exposure in labs or course activities. This very high exposure rate (99%) may help explain the high average confidence to learn and high adaptation intention reported later in the Results.

We also show a simple visual summary of the sample composition. Figure 6A presents the number of respondents by year of study.

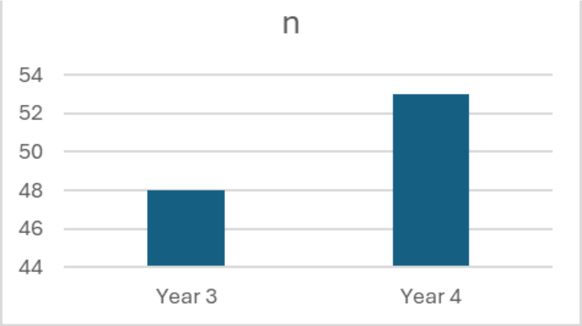

Figure 6A.: Sample distribution by year of study (N = 101)

Figure 6B shows the number of respondents by employment status.

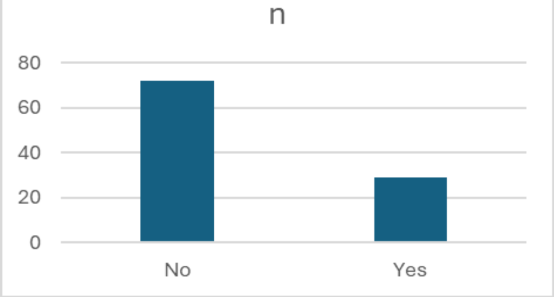

Figure 6B: Sample distribution by employment status (N = 101)

4. Discussion

This study looked at how robotics students think about working with a collaborative robot. The results are simple and clear.

First, the scales worked well. The reliability values were acceptable for short 3-item scales. This means the items in each scale matched each other and can be used as one score (TRUST, ORG, RISK, ADAPT).

Secondly, students reportedly indicated a strong expectation for safety help and a high desire to adapt. A significant number of students expressed their willingness to engage in a collaborative robot environment. They anticipated explicit protocols and training. This indicates a favorable outlook for future HRC uptake, particularly among this student cohort.

The most significant associations with adaptation were trust, anticipated assistance, and confidence in learning. The correlation findings indicated a clear relationship between ADAPT and TRUST, ORG, and SELFCONF. RISK had a tenuous connection with ADAPT when examined in isolation.

All four predictors in the regression model had positive coefficients. SELFCONF emerged as the most significant predictor, following by TRUST and ORG. This indicates that several pupils are prepared to adjust when they perceive their competence and have confidence in the robot. Anticipated training and protocols are also significant.

A significant aspect is RISK. In the basic correlations, RISK was not associated with ADAPT. In the regression analysis, RISK emerged as a minor positive factor. This suggests that "awareness of risk" is not always an impediment. Certain students may see themselves as prepared to adjust while recognizing potential risks. Risk awareness and preparedness may coexist.

Employment status was also significant. Unemployed students had elevated levels of TRUST and ADAPT compared to their employed counterparts. Employed students may exhibit more caution due to their practical job experience. This does not imply a disdain for robots. It may indicate that they contemplate everyday limitations and hazards in the workplace.

The hierarchical regression corroborates the same concept. TRUST and SELFCONF explained the majority of ADAPT initially. ORG subsequently included a little but distinct additional component. RISK also included a little supplementary component. This indicates that preparedness is mostly individual (trust and confidence), although it is also contingent upon students' expectations of an organization (training and processes).

4.1. Practical Meaning

To adequately prepare students for HRC, institutions must provide instruction beyond just robot programming. Instruction should include safe work practices, interpretation of robotic behavior, and composed risk management techniques. Explicit instruction and well-defined regulations may foster trust. Confidence increases when students engage with and comprehend the system.

4.2. Limits of this Study

This research included a brief online questionnaire and a singular scenario narrative. It assessed intents and expectations rather than actual behavior inside a production setting. The sample originated from a single program and mostly consisted of males. Furthermore, almost all students indicated previous experience to robots, which may enhance confidence and adaption ratings. Consequently, outcomes may vary across different groups.

4.3. Future Work

Subsequent research may include participants from many engineering disciplines as well as non-technical domains. They may compare various HRC situations (e.g., predictable vs unexpected robot movements) and evaluate training modules before and after a course.

5. Conclusions

This research examined the perceptions of robotics students about risk and adaptability within a human-robot cooperation context. We used a brief anonymous poll and conducted basic analysis using JASP. The four brief measures (TRUST, ORG, RISK, and ADAPT) demonstrated satisfactory reliability, indicating that the items functioned cohesively and could be used as composite scores.

Students indicated a strong expectation of safety help and a high desire to adapt. Intention to adapt was greater when students expressed increased trust in the robot, heightened expectations of safety assistance (including explicit protocols and training), and elevated confidence in their learning capabilities. In the regression model, confidence in learning emerged as the most significant predictor of adaptation intention, followed by trust and anticipated safety support. The perceived risk had a little positive impact in the regression analysis, indicating that risk awareness did not consistently diminish preparedness within this student cohort.

Employment status was also significant. Unemployed students exhibited more trust and a stronger desire to adapt compared to their employed counterparts. This suggests that students with job experience may exhibit more caution or a more pragmatic perspective toward workplace changes and hazards. The hierarchical regression corroborated the same overarching conclusion. Trust and confidence mostly accounted for adaptation, whereas anticipated support and risk contributed somewhat.

In conclusion, several students are prepared to collaborate with cobots when they possess faith in the robot, confidence in their ability to study, and anticipate explicit instruction and guidelines. These findings may assist universities and prospective employers. Training must foster trust and confidence while articulating risks in a clear and composed manner. Clear protocols and safety measures must be comprehensible, ensuring that prospective engineers are well prepared prior to entering automated environments.

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References

[1] Arents, J., Abolins, V., Judvaitis, J., Vismanis, O., Oraby, A., & Ozols, K. Human–robot collaboration trends and safety aspects: A systematic review. Journal of Sensor and Actuator Networks 2021, 10(3), 48. https://doi.org/10.3390/jsan10030048

[2] Boncătă, A.-E., Nechita, R.-M., Ulerich, O., & Cristoiu, C. Transforming Libraries. The Role of Autonomous Robots in Sorting, Inventorying, and Book Search. International Journal of Mechatronics and Applied Mechanics 2024, 87–95. https://doi.org/10.17683/ijomam/issue17.10

[3] Berx, N., Adriaensen, A., Decré, W., & Pintelon, L. Assessing system-wide safety readiness for successful human–robot collaboration adoption. Safety 2022, 8(3), 48. https://doi.org/10.3390/safety8030048

[4] Wu, J., Ren, J., Ravn, O., & Nalpantidis, L. A risk-informed design framework for functional safety system design of human–robot collaboration applications. Safety 2025, 11(1), 24. https://doi.org/10.3390/safety11010024

[5] SMBPB, S., Valori, M., Legnani, G., & Fassi, I. Assessing safety in physical human–robot interaction in industrial settings: a systematic review of contact modelling and impact measuring methods. Robotics 2025, 14(3), 27. https://doi.org/10.3390/robotics14030027

[6] Khan, A., Akhtar, M., Qureshi, S. M., Mustafa, M., Alsaleh, N. A., & Ahmad, I. A Systematic Review of Safety-Driven Approaches in Human–Robot Collaborative Systems. Sensors 2026, 26(7), 2079. https://doi.org/10.3390/s26072079

[7] Qixiang, C., Jinmin, H., Zhou, X., Shuaijie, Z., et al. A Comprehensive Review of Human-Robot Collaborative Manufacturing Systems: Technologies, Applications, and Future Trends. Sustainability 2026, 18(1), 515. https://doi.org/10.3390/su18010515

[8] Firmino de Souza, D., Sousa, S., Kristjuhan-Ling, K., et al. Trust and trustworthiness from human-centered perspective in human–robot interaction (HRI)—A systematic literature review.

Electronics 2025, 14(8), 1557. https://doi.org/10.3390/electronics14081557

[9] Zhu, Y., Wang, T., Wang, C., Quan, W., & Tang, M. Complexity-driven trust dynamics in human–robot interactions: Insights from ai-enhanced collaborative engagements. Applied Sciences 2023, 13(24), 12989. https://doi.org/10.3390/app132412989

[10] Rahman, S. M. Trust-Based Modular Cyber–Physical–Human Robotic System for Collaborative Manufacturing: Modulating Communications. Machines 2025, 13(8), 731. https://doi.org/10.3390/machines13080731

[11] Prahl, A. Mortal vs. Machine: A Compact Two-Factor Model for Comparing Trust in Humans and Robots. Robotics 2025, 14(8), 112. https://doi.org/10.3390/robotics14080112

[12] Ali, H.A., Goga, N., Vasilăteanu, A., Muslim, A.M., Ali, K.A., Drăgoi, M.-V. English and Romanian Brain-to-Text Brain-Computer Interface Word Prediction System. IJACSA 2022, 13(10). DOI:10.14569/IJACSA.2022.0131003

[13] Drăgoi, M.-V., Hadăr, A., Goga, N., Grigore, L.-Ș., Ștefan, A., Ali, H.A. Design and Implementation of an EEG-Based BCI Prosthetic Lower Limb Using Raspberry Pi 4. U.P.B. Sci. Bull., Series C 2023, 85(3), 353–366.

[14] Drăgoi, M.-V., Hadăr, A., Goga, N., et al. Contributions to the Dynamic Regime Behavior of a Bionic Leg Prosthesis. Biomimetics 2023, 8, 414. https://doi.org/10.3390/biomimetics8050414

[15] Gamazeliuc, G., Nechita, R.-M., Ulerich, O., Bădiță-Voicu, L.-L., & Cristoiu, C. Fusion of AI and Robotics for Transforming Neurosurgery. International Journal of Mechatronics and Applied Mechanics 2024. https://doi.org/10.17683/ijomam/issue18.21

[16] Drăgoi, M.-V., et al. Real-Time Home Automation System Using BCI Technology. Biomimetics 2024, 9, 594. https://doi.org/10.3390/biomimetics9100594

[17] Drăgoi, M.-V., et al. Interactive Teleoperation of an Articulated Robotic Arm Using Vision-Based Human Hand Tracking. Biomimetics 2026, 11, 151. https://doi.org/10.3390/biomimetics11020151

[18] Cristoiu, C.A., Drăgoi, M.-V., Nechita, R.-M., et al. The Impact of Geometric Continuities (C1, C2, and C3) on the Trajectories of Industrial Robots. Technologies 2026, 14, 176. https://doi.org/10.3390/technologies14030176

[19] Tălîngă, A.-M., Hadăr, A., Drăgoi, M.-V., et al. YOLO-v8 in Capturing Imperfections Generated by Changing 3D Printer Parameters. U.P.B. Sci. Bull., Series C 2024, 86(4), 253-266.

[20] Drăgoi, M.-V., Afram, R.M., Alzubaidi, A.A.A.M.H., et al. Comparative Analysis of Interpolation and Extrapolation Methods in Regression Models. U.P.B. Sci. Bull., Series C 2026, 88(1), 145-160.

[21] Nechita, R.-M., Deselnicu, D.-C., Băjenaru, V.-D., et al. Optimizing Material Recovery from Photovoltaic Waste: A Performance Ranking Using Hybrid BWM-PROMETHEE II. Sustainability 2026, 18(8), 3750. https://doi.org/10.3390/su18083750

[22] Drăgoi, M.-V., Maier, A.N., Alzubaidi, A.A.A.M.H., et al. Multithreading VPN Application to Monitor Web Traffic and Unblock Geoblocking Websites. U.P.B. Sci. Bull., Series C 2025, 87(4), 217-232.

[23] Nechita, R.-M., & Cristoiu, C. A Systematic Review of Digital Twin Applications in Industry 4.0: Sector Specific Insights. International Journal of Mechatronics and Applied Mechanics 2025, 1, 173–185. https://doi.org/10.17683/ijomam/issue21.17

[24] Tălîngă, A.-M., Baciu, F., Hadăr, A., et al. Numerical and Experimental Study of a Sandwich Beam Subjected to a Three Points Bending Test. U.P.B. Sci. Bull., Series D 2025, 87(3), 227-240.

[25] Drăgoi, M.-V., Nisipeanu, I., Puiu, R.-A., et al. An Inclusive Offline Learning Platform Integrating Gesture Recognition and Local AI Models. Biomimetics 2025, 10(10), 693. https://doi.org/10.3390/biomimetics10100693

[26] Drăgoi, M.-V., Puiu, R.-A., Petrea, G., et al. Improving the Learning Process for Students: Personalizing Learning through Software Applications. U.P.B. Sci. Bull., Series C 2025, 87(1), 157-166.

[27] Buzducea (Drăgoi), C.-A., Drăgoi, M.-V., Cristoiu, C., et al. Machine Learning in Education: Predicting Student Performance and Guiding Institutional Decisions. Educ. Sci. 2026, 16(1), 76. https://doi.org/10.3390/educsci16010076

[28] Drăgoi, M.-V., Puiu, R.-A., Petrea, G., Cristoiu, C.A., Dumitrescu, C.-I. Willingness to Allow Educational Data Use for Learning Analytics in Higher Education: Trust and Governance Predictors: An Exploratory Study. Educ. Sci. 2026, 16(4), 637. https://doi.org/10.3390/educsci16040637

[29] Neagu, S.N., Vieriu, A.M. Digital and Psychological Well-Being Among Technical University Students: Exploring the Impact of Digital Engagement in Higher Education. Educ. Sci. 2025, 15(9), 1192. https://doi.org/10.3390/educsci15091192

[30] Vieriu, A.M., Petrea, G. The Impact of Artificial Intelligence (AI) on Students' Academic Development. Educ. Sci. 2025, 15(3), 343. https://doi.org/10.3390/educsci15030343

[31] Anghel, G.A., Zanfir, C.M., Matei, F.L., Voicu, C.D., Neacșa, R.A. The Integration of Artificial Intelligence in Academic Learning Practices: A Comprehensive Approach. Educ. Sci. 2025, 15(5), 616. https://doi.org/10.3390/educsci15050616

[32] Esposito, G., Sanchez, M., Fratini, F., et al. Embedding AI Ethics in Technical Training: A Multi-Stakeholder Pilot Module Emphasizing Co-

Design and Interdisciplinary Collaboration at Rome Technopole. Educ. Sci. 2025, 15(10), 1416. https://doi.org/10.3390/educsci15101416

[33] Vieriu, A.M. Inclusive Education as a Pillar of Sustainability: An Experimental Study on Students' Attitudes Towards People with Disabilities. Educ. Sci. 2025, 15(11), 1522. https://doi.org/10.3390/educsci15111522

[34] Vieriu, A.M., Hainagiu, S.M. Perfectionism and Workaholism as Barriers to Lifelong Learning and Occupational Sustainability: A Cross-Professional Analysis. Sustainability 2025, 17(4), 6512. https://doi.org/10.3390/su17146512

[35] Nechita, R.-M., & Nechita, M.-I. Ethical Design in Medical AI Robotics: Between Innovation and Responsibility. Robotica & Management 2026, 30, 27–32. https://doi.org/10.24193/rm.2025.2.5

[36] Neagu, S.N., Vieriu, A.M. Challenges and Strategies for Time Management among Students in the Technological Era. In EDULEARN25 Proceedings 2025, 1473–1481. DOI: 10.21125/edulearn.2025.0464

[37] Choi, S., & Park, S. Governmental Transformation in the Era of the Post Pandemic: Analyzing the Impacts of the Pandemic on Organizational Cultural Change in Government. Public Organization Review 2023, 23, 451–467. https://doi.org/10.1007/s11115-023-00703-7

[38] Neagu (Hodrea), R.A., Vieriu, A.M., Ionescu, S.C. Exploring the Educational Value of Pandemic-Driven Data Protection Insights: A Research Study. In EDULEARN24 Proceedings 2024, 4024–4033. https://doi.org/10.21125/edulearn.2024.1012

[39] Badea Sorin Ionut (2021) Analysis of current methods for leakage part detection International Journal of Mechatronics and Applied Mechanics Article *Open Access* DOI: 10.17683/ijomam/issue10/v2.13 *Part of* ISSN: 2559-4397 *Part of* ISSN: 2559-6497

[40] Gheorghe, G., Sorin-Ionut, B., Ilie, I., Veronica, D. (2022). Original Constructive Solutions for the Development of Industry 4.0 in Romania. In: Machado, J., Soares, F., Trojanowska, J., Yildirim, S. (eds) Innovations in Mechatronics Engineering. icieng 2021. Lecture Notes in Mechanical Engineering. Springer, Cham. https://doi.org/10.1007/978-3-030-79168-1_25

[41] Alexandru Costin Ciobanu, Andreea Dana Alionte, Liviu Marian Ungureanu, Cristian Gabriel Alionte, Iulian Sorin Munteanu, Sorin Ionut Badea. A simple educational intelligent speed detection system for road vehicules. International Journal of Mechatronics and Applied Mechanics 2022, no. 12, pag 6–12. https://doi.org/10.17683/ijomam/issue12.1

[42] M. Spirescu, S. Dumitru, A. Constantinescu, C. Badea. Human robots safe cooperation in an integrated approach. International Journal of Mechatronics and Applied Mechanics 2017, no. 2, pag 139–144, ISSN 2559-4397.

[43] Badea Cristian Radu. Study of the influence of contact points, scenarios and graphical reference elements on the motion analysis process, carried out using the inertial mechatronic system mvn analyze. International Journal of Mechatronics and Applied Mechanics, 2019, issue 6, vol II, pag 74–82, ISSN 2559-4397. https://doi.org/10.17683/ijomam/issue6.37