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Abstract

Automation, digitalization, and, more recently, generative artificial intelligence (gAI) are changing the skill sets employers demand. However, understanding remains limited about how different sector-level stakeholders in developing countries perceive these innovations, and about these technologies' impact on university graduates' employability. The comparative qualitative study draws on 60 interviews with graduates, employer representatives and academics, five of each type per sector, in four Bangladeshi sectors (readymade garments and textiles (RMG); information and communication technology and IT-enabled services (ICT/ITES); banking and financial services; logistics and supply chain management), as well as multi-sector comparative data. Reflexive thematic analysis yielded cross-sector themes, which include framing of technology and specific discussion of AI in ICT/ITES, disciplinary expertise being necessary but no longer sufficient, with digital, data and adaptive capabilities increasingly essential and learned largely outside formal programmes, cross-sector problems with institutional coordination due to curricula lag (the mode and extent of lag varies according to discipline), reasons why these results should not be taken as an indication of job loss and the impact of gAI, as well as sector-specific and generic implications for universities, sectors and employer associations with clear links to the data. Shortcomings include reliance on perceptions, small cell sizes across multiple parameters, and a lack of a worker perspective.

Keywords: Automation; Digitalization; Generative AI; Graduate Employability; Skills Mismatch; Bangladesh

1. Introduction

In technology, the skills labor markets value have always evolved. Autor, Levy and Murnane (2003)'s task-based framework asserts that computers replace routine, codifiable tasks and support non-routine analytical and interactive tasks. Generative AI extends this to drafting, coding, and analysis. Eloundou

et al. (2024) suggest that 80% of the US labor force has at least 10% of tasks eligible for impacts from generative pre-trained transformers. Most evidence arises from advanced economies, which cannot be naïvely extrapolated onto developing countries. In the former, the World Bank (2026) finds a much higher proportion of jobs vulnerable to substitution by generative AI than in high-income economies. However, augmentation benefits require information technology infrastructure and skills.

Bangladesh is also an interesting context for this question. Four-fifths of exports are in the ready-made garments (RMG) sector, and press reports anticipate widespread automation of factory tasks. These estimates are not peer-reviewed. They also apply to workers, helpers, and operators, not graduates, so their implications for graduates' prospects are indirect: graduates design, direct, and control the labour force, but that design, direction, and control run through the helper and operator tiers to reach them. Conversely, the Smart Bangladesh ICT Master Plan 2041 foresees demand for digital skills across the economy (ICT Division 2023), so graduates face labor markets where automation, digitization, and artificial intelligence arrive at different times and places.

Existing Bangladeshi research documents an existing skills mismatch between university provision and workforce needs (Hossain & Arefin, 2025). No comparative qualitative research has examined graduates', employers', and academics' perceptions of technology-driven change and its implications for graduate employability across sectors. This statement is based on non-systematic searches of Scopus, Google Scholar, and grey literature, combining keywords such as automation, digitalization, artificial intelligence, skills, graduate employability, curriculum, Bangladesh, and qualitative. Last searched in August 2026. Qualitative research in Bangladesh remains limited; for example, a study of micro-credentials draws on 19 key informant interviews (Sarker et al., 2026).

This paper explores that discrepancy in three ways. Empirically, it compares views across three stakeholder types and four sectors, and explicitly asks whether people refer to AI or to automation and digitalization more broadly. Analytically, it develops four themes and a proposition about programme-level readiness for future research. Practically, it links the recommendations, the findings, and the actors who might act on them. This is an exploratory, interpretive study. It captures perceptions, and "shift" throughout thus refers to perceived change over roughly the past two or three years, not change.

2. Background and Conceptual Framing

2.1 Key concepts

The literature and the interviews use "AI", "automation" and "digitalization" interchangeably, yet they imply different mechanisms for skill demand. Table 1 sets out the definitions used in this paper. The research cannot distinguish between the effects of AI and those of digital transformation more generally and does not aim to

Table 1 Definitions of key terms

Term	Definition used in this paper
Automation	Use of machines or software to carry out tasks previously done by people, typically following pre-specified rules (Acemoglu and Restrepo 2019).
Digitalisation	Adoption of digital tools, platforms and data systems that change how work is organized, without necessarily replacing tasks.
Artificial intelligence (AI)	Systems that perform tasks associated with human cognition, such as prediction, classification or content generation, by learning from data. Generative AI produces text, code or images.
Programme readiness	Capacity of a university programme to update content, build staff capability, provide infrastructure and sustain employer links so that graduates acquire technology-related competences. Analyzed here at programme and department level, not for whole institutions or individuals.
Graduate digital and AI literacy	An individual's competence to use, evaluate and work alongside digital tools and AI (Long and Magerko 2020). Treated as separate from programme readiness.
Perceived graduate employability	Stakeholders' views on graduates' capacity to obtain and keep work suited to their qualification, understood through the graduate-capital view (Tomlinson 2017). No employment outcomes were measured.
Recent graduate	A person who graduated within three years of interview and was employed in, or seeking work in, the sector.
Employer representative	A manager with responsibility for hiring, workforce planning or skill development (HR managers, recruitment professionals, department managers and organizational decision-makers).
Academic staff	Faculty teaching in the discipline most closely aligned with the sector (for example textile engineering, computer science, finance, supply chain management).

2.2 Task-based technological change and occupational exposure

Early descriptions of skill-biased technological change suggested that technology increases demand for educated workers relative to uneducated workers (Katz & Murphy, 1992). This task-based approach extended this idea by distinguishing between routine and non-routine tasks (Acemoglu & Autor, 2011; Autor et al., 2003) and offering insights into job polarization in advanced economies (Autor & Dorn, 2013; Goos et al., 2014). Acemoglu and Restrepo (2018, 2019) introduced a displacement-reinstatement model, in which automation both displaces and reinstates tasks, and the overall impact on skill demand depends on the relative extent of each.

Sector-level exposure studies differ. Frey and Osborne (2017) found that computerization could make 47 per cent of workers in the US redundant, based on reducing engineering constraints like perception and manipulation, creative intelligence, and social intelligence. Many follow by identifying lower task-level risk estimates, but task heterogeneity within occupations makes occupations look overexposed; for OECD countries, Arntz et al. (2016) identify this issue when looking at work at the task level. Felten et al. (2021) develop an AI-specific exposure metric. A previous study by Brynjolfsson et al. (2025) also estimates relative employment losses for young workers in the United States across job categories most exposed to AI, highlighting the importance of focusing on entry-level jobs. However, these US estimates may not extend to other countries, such as Bangladesh.

2.3 Developing-country exposure and the Bangladeshi context

Estimates of developing-country exposure are based on somewhat different grounds. Chang et al. (2016) considered textiles, clothing, and footwear, which emerged as the most vulnerable sectors across five ASEAN economies (Cambodia, Indonesia, the Philippines, Thailand, and Viet Nam), but not Bangladesh. The more granular ILO index indicates that generative-AI exposure is concentrated in clerical and other digitally delivered cognitive work (Gmyrek et al., 2025). Both the World Bank (2026) and Gmyrek et al. (2026) note that developing-country exposed workers are generally already online, while those able to benefit from augmentation are generally not, a familiar phenomenon in diffusion and TQE (technology, organization and environment) literatures (Rogers, 2003; Tornatzky

and Fleischer 1990), and so technical exposure does not automatically lead to changes in the workplace.

Four Bangladeshi sectors are analyzed. In RMG exports, approximately US$39 billion in FY2024-25 accounted for about 81% of total exports (Financial Express, 2025; Textile Focus, 2025), and the sector employs about four million workers (Rumi et al., 2021). Media and industry sources suggest a maximum of 60% of the RMG workforce could be displaced by 2030 (Daily Star, 2019), and that at the factory level, automation drove a 30% decrease in employment in 2023, with the greatest impact on the operators hired as helpers, rather than trainees (LightCastle Partners, 2025). These figures are estimates, not peer-reviewed statistics, and refer to operatives. Bangladeshi graduates in the sector held roles in production planning, quality assurance, industrial engineering, merchandising, and textile engineering; Online Resource 2 identifies the roles of RMG graduate participants. Their exposure is therefore indirect: through changes to the operative workforce they supervise, and through the digitalization of planning and monitoring tools. Peer-reviewed evidence links automation and reshoring to employment pressure in Bangladeshi apparel (Hoque et al., 2022).

ICT/ITES will also merge software development with outsourced and business-process work, which is more routinized and, the author argues, is "likely to be highly exposed to generative AI". Banking overlaps with fintech, and logistics with RMG supply chains. Evidence on these two sectors is thinner: a survey of Bangladeshi manufacturing supply chains suggests that infrastructure, cost, and skills limit digital technology adoption (Tasnim et al., 2023).

Other factors also influence employment and skill demand and provide alternative explanations for any alleged shift. These factors include Bangladesh's scheduled graduation from least-developed-country status in November 2026 (the government lobbied for a three-year postponement of the preparatory period, which the UN Committee for Development Policy endorsed, so the time of graduation was uncertain at time of writing; the UN Economic and Social Council advised on 21 July 2026 that the UN General Assembly make the final decision before 24 November 2026, but no UN General Assembly decision had been publicized by end of September 2026; Bangladesh (Sangbad Sangstha, 2026), tariff reforms in export markets, and the 2024 political transition. Policy tools related to these issues are the Smart Bangladesh ICT Master Plan 2041 (ICT Division 2023), draft National

AI Policy 2026-2030 (ICT Division 2026), UGC, university Institutional Quality Assurance Cells (IQACs) created by the Higher Education Quality Enhancement Project, the Bangladesh National Qualifications Framework (BNQF), and the National Skills Development Authority (NSDA).

2.4 Graduate employability and skills mismatch

Human capital theory treats education as an investment in productivity/earnings (Becker, 1964). Mismatch enters the model when curricula depart from employer needs, creating a skills mismatch. McGuinness et al. (2018) identify horizontal versus vertical mismatch, skill gaps, skill shortages and skill obsolescence. The last two become prominent when technology transforms the nature of work. Critics have argued that supply-side explanations are partial; Dacre Pool and Sewell (2007) and Yorke (2006) stress that employability depends on a complex interplay of skills, experience, self-concept, and context; Brown et al. (2003) argue that low-quality jobs drive skills mismatches and skill surpluses, a positional-competition story. Tomlinson (2017) sees employability as incorporating human, social, cultural, identity, and psychological capital.

This paper uses employability in its generalized, relational sense. However, the data reveal a more limited issue: how stakeholders characterize graduate learning, and to what extent degree programmes meet those expectations. This paper does not address employability in terms of social or cultural capital, gender, or economic background, although these issues are pertinent to the Bangladeshi literature (Hossain & Arefin, 2025). The McGuinness taxonomy is applied only descriptively in the Discussion, not as an analytical coding framework.

2.5 The curriculum–industry gap in Bangladesh

Bangladeshi studies on education and skills have been limited for some years. Hossain and Arefin (2025) interviewed 450 graduates, employers, and academics, then quantified 'perceived employment readiness' with a new model that placed attitude and skills on one side and employer preference for foreign workers and socioeconomic factors on the other. Skills and skills training positively influenced employment readiness; the other factors showed mixed results. Only one-third of the 'employability' survey sample and less than 40% of all Bangladeshi universities provided work-based internship programmes; these figures could not be checked against UGC figures. Subsequent research

is largely consistent. Alam et al. (2022) and Hosain et al. (2021) say skills training provision was patchy and employers overemphasized technical skills. Hasan et al. (2024) find intermediate course structure and institutional 'fit' only partially mediate quality and employability skills. Alam and Ogawa (2024) report that remote graduates' ICT skill levels exceed available infrastructure, while Sarker et al. (2026) say micro-credentials are not well known or embedded. Kabir and Kamal (2023) describe skills mismatch in the leather sector. Developments in Morocco (Draissi et al., 2023) and Malaysia (Tee et al., 2024) show similar patterns.

The literature is sector-neutral and based on surveys; there is not much on whether the gap varies by sector or how technology-enabled change is described by those experiencing it. The literature also offers little on how those experiencing it perceive technology-driven change. WEF (2025) predicts AI/big-data skills will be among the fastest-growing core skills by 2030; therefore, the question matters.

2.6 Programme readiness and graduate digital and AI literacy

A different line of research explores the conditions under which education systems change with technology. The TOE framework argues that adoption depends on technological, organizational, and environmental conditions (Tornatzky & Fleischer, 1990), while absorptive-capacity theory holds that organizations need relevant prior knowledge to take advantage of new knowledge (Cohen & Levinthal, 1990). In higher education, evidence points to mixed levels of readiness. A 2026 global survey found institutions falling short of the leadership vision (IREX and Development Gateway 2026), and a review of generative-AI policy at leading universities identified broad differences in approach (Jin et al., 2024). The UNESCO competency framework for teachers can inform faculty skill levels (Miao & Cukurova, 2024), and Singh et al. (2026) draw on it to develop an approach to integrating AI literacy into digital-literacy training courses in developing nations.

Programme-level readiness and graduates' individual digital and AI literacy are separate concepts (Table 1; Long & Magerko, 2020). A national-level policy commitment should not be expected to generate either. The five readiness factors presented in Section 4.5 were evolved from the interview data and compared with the TOE categories in the Discussion.

2.7 Research gap, aims and research questions

This research contributes as follows. Our contribution is a comparative, sector-differentiated qualitative account of graduates', employers', and academic opinions on the nature and impact of technology-led skill change on employability in Bangladesh. Figure 1 shows the sensitizing framework used to construct the interview guides and the initial interpretation of the data; this is not a test of the model. Readiness to deliver programmes and graduate digital and AI capability are proposed as distinct mediating factors influencing the strength of the relation between skill shift, curriculum gap, and employability.

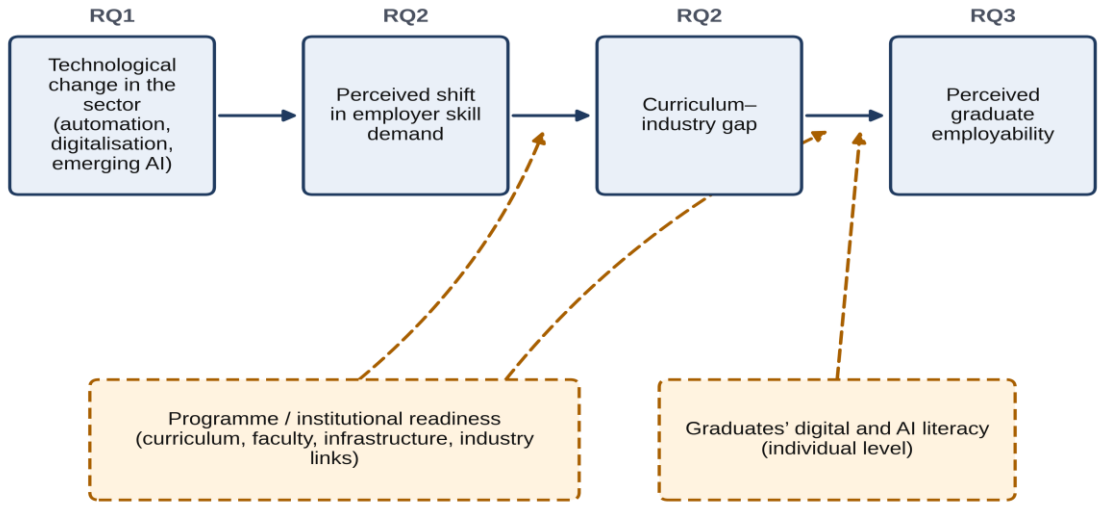


Fig. 1 Sensitising framework and research questions. The framework is not a tested model. Constructs are labelled; RQ tags sit above the boxes they address. Dashed arrows land on the links that the conditioning factors examined in RQ3 might affect

The study addresses four research questions:

RQ1. How do graduates, employer representatives and academic staff in four sectors (RMG, ICT/ITES, banking and financial services, and logistics and supply chain management) describe technological change in their field, and where do they name AI explicitly rather than automation or digitalization?

RQ2. How do these stakeholders perceive the resulting shift in skill demand, and how does this shift relate to the curriculum–industry gap within each sector?

RQ3. How do stakeholders' accounts link programme readiness and graduates' digital and AI literacy to graduates' employability prospects within each sector?

RQ4. What patterns of convergence and divergence emerge across the four sectors?

3. Methodology

3.1 Design and epistemological position

Study design: Comparative qualitative interview study with three stakeholder groups in four sectors. The sectors are intended as comparison contexts, not bounded cases: there is no within-case logic of replication; literal or theoretical replication is claimed; the sectors were selected as contrasting comparison contexts, and a small number of organizations and universities in each is insufficient to constitute a bounded case. The design was selected because the research questions focus on individuals' experiences of technological change, and because cross-sector and cross-stakeholder comparisons reveal similarities and differences.

The study adopts a conceptualist stance: "participants' accounts are epistemologically viewed as local understandings of work and institutions, rather than as measures of technological change and its consequences", and this approach uses reflexive thematic analysis (Braun and Clarke 2006, 2019, 2022). This work followed the Standards for Reporting Qualitative Research (O'Brien et al., 2014).

3.2 Sector selection

Four sectors were purposively selected for variation in these parameters of technological change and for the presence of large graduate employers: RMG (readymade garments) was Bangladesh's largest export sector; ICT/ITES was the strategic sector of the national digital agenda; banking/financial services was a large graduate employer where digitalization of core business processes was visible; and logistics/supply-chain management was a digitalizing activity with a close link to export manufacturing. Other large graduate sectors, including health and public administration, were outside the study's remit. The study defined ICT/ITES as software development and the use of IT-enabled services, including business-process

outsourcing (BPO) companies; RMG/Textiles as apparel and textile manufacturing, including integrated spinning, weaving, and dyeing mills.

Table 2 presents the sector-specific exposure profiles anticipated prior to fieldwork, the evidence used to derive each profile, and how the profiles were subsequently revised in light of the findings. They were assumptions, not facts, to be tested.

Table 2 Sector selection: working assumptions, supporting evidence and refinement after fieldwork

Sector	Working assumption before fieldwork	Supporting evidence	Refinement after fieldwork (Section 4)
RMG/textiles	High pressure for task restructuring in factory work	Textiles, clothing and footwear among the most automation-susceptible sectors in five ASEAN economies (Chang et al. 2016); press and industry estimates for Bangladesh (caveated in Section 2.3)	Participants described task change and skill upgrading, not AI; no accounts of graduate job loss. "High displacement" was dropped as a label.
ICT/ITES	High AI adoption with augmentation of software work; routine outsourcing tasks may be exposed	National digital strategy (ICT Division 2023); clerical and digitally delivered work most exposed to generative AI (Gmyrek et al. 2025)	AI named explicitly and framed as augmentation; outsourcing work was not distinguished in the extracts.
Banking and financial services	Mixed: back-office automation alongside new digital roles	Clerical exposure to generative AI (Gmyrek et al. 2025); little Bangladesh-specific evidence	Described as process and role transformation; AI linked in summaries to fraud detection, analytics and risk.
Logistics and supply chain	Early-stage adoption	Adoption constrained by infrastructure, cost and skills in manufacturing supply chains (Tasnim et al. 2023)	Confirmed as digitalization constrained by infrastructure and skills; AI in forecasting mentioned in summaries.

Note. Exposure labels are working assumptions used for case selection, not findings.

3.3 Participants, inclusion criteria and sampling

Participants were selected through purposive maximum-variation sampling and snowball referral through gatekeepers (association-affiliated HR networks, department contacts). Inclusion criteria are listed in Table 1. Graduates were included if their education differed in duration and attendance, employment status, and so on; employer representatives from organizations at various levels of digital adoption (incubated / mainstream / experienced); and academic staff from each appropriate department. Four to six in each group in each sector were planned, and five in each of 12 cells took part, giving 60 participants (Table 3).

Table 3 Participants by sector and stakeholder group

Sector	Graduates	Employer representatives	Academic staff	Total
RMG/textiles	5	5	5	15
ICT/ITES	5	5	5	15
Banking and financial services	5	5	5	15
Logistics and supply chain	5	5	5	15

Sector	Graduates	Employer representatives	Academic staff	Total
Total	20	20	20	60

Because each cell includes five participants, we do not claim saturation. Instead, we justify the sample size through information power (Malterud et al., 2016): the aims are narrow, the participants are highly relevant to the questions, the interviews were focused, and the analysis compares across groups. Guidance on code saturation derived from homogeneous samples (Guest et al., 2006) is not relevant to cells of five, and meaning-based definitions of saturation are debated (Braun & Clarke, 2021; Hennink et al., 2017). Claims at the cell level are therefore tentative.

Better-networked organizations and universities, those more willing to be included in the research, and those based in or near Dhaka were easier to access; read the data with this in mind. Online Resource 2 provides the number and location of organizations and universities (all sectors), their public or private status, firm size and export focus (employers only), and years since graduation (graduates only). We did not keep a systematic record of refusals; therefore, we have no refusal rate. Snowball referral was used to identify willing eligible participants through appropriate networks; however, it was not analyzed as a network process, and the number of referral steps was not traced. The degree of selection bias is therefore unquantifiable (see Section 6).

3.4 Data collection

Team members conducted face-to-face, online, and telephone interviews in Bangla and English. Before ethics approval (12 November 2025) and before main data collection, the team piloted the guides with 15 participants to test and refine question wording, sequence, and follow-up probes. These pilot interviews did not contribute to the final sample of 60 and were not analyzed. All interviews lasted 30–45 minutes, were audio-recorded with participants' permission, and were transcribed verbatim. The three guides developed for each stakeholder relate to five dimensions of technological change (skill shift, curriculum-industry mismatch, digital/AI literacy and institutional readiness, and graduate employability) and were then built in follow-up interviews to explore sector-specific nuances. We wrote a reflective field note after each interview.

Some prompts assumed technological change (such as 'where do you notice AI tools or automated systems'), which could prompt participants to give more AI responses. To avoid leading prompts, the

initial questions in each guide asked what the participant did, and probes then elicited examples in the participants' own words. This approach risks leading, which we discuss in Section 6. We prepared transcripts in the interview language (Bangla or English). The authors (bilingual in English and Bangla) translated Bangla passages into English and then checked them against the audio recordings. Quotations in Section 4 were lightly edited in terms of syntax (for example, to improve clarity) and to adapt to UK spelling conventions.

3.5 Data analysis

Transcripts and notes from interviews were analyzed using the reflexive thematic analysis framework (Braun and Clarke 2006, 2019, 2022). NVivo 14 (Lumivero) was used to index and line code the textual data. The analysis occurred following Braun and Clarke's six recursive stages: familiarizing; coding; generating initial themes; developing and reviewing themes; defining and naming themes; and writing up. The five interview dimensions helped guide the structure of the analysis. The analysis was therefore framework-oriented, rather than purely inductive. Codes were generated from the transcripts and then crossed within and across the dimensions to create themes that spanned the structure of the guide.

Two authors coded an initial subset of 10 transcripts. They discussed differences to support reflexive discussion, refine code definitions, strengthen the coherence of analysis, and broaden interpretation rather than to produce measures of agreement. One author coded the remaining 50 transcripts. In keeping with the principles of reflexive thematic analysis, we do not report coding as an index of reliability. The author maintained reflexive memos and an audit trail of analytic decisions throughout. The study was assessed against Braun and Clarke's (2022) and Tracy's (2010) criteria: a worthwhile topic, rich rigour, sincerity through reflexive memoing, credibility through three stakeholders' vantage points, resonance, an important contribution, ethical practice, and meaningful coherence.

To compare sectors, we compiled results in a case-ordered meta-matrix (Miles et al., 2014). We compared accounts of the three stakeholder groups within each sector before comparing

the sectors. To address RQ1, we re-read each extract and recorded where participants explicitly used AI terms and where they described automation, software, or digital systems. Table 4 indicates which stakeholder groups provided information for each research question. Fig. 2 summarizes the study design and analytic process.

Table 4 Interview coverage by research question

Research question	Primary evidence
RQ1: technological change (AI, automation, digitalization)	Graduates, employer representatives, academic staff; comparison across sectors
RQ2: skill-demand shift and the curriculum–industry gap	Employer representatives and graduates for skill demand; academic staff for curriculum constraints
RQ3: readiness, digital and AI literacy, and employability	All three groups
RQ4: convergence and divergence across sectors	Cross-sector meta-matrix (Table 7)

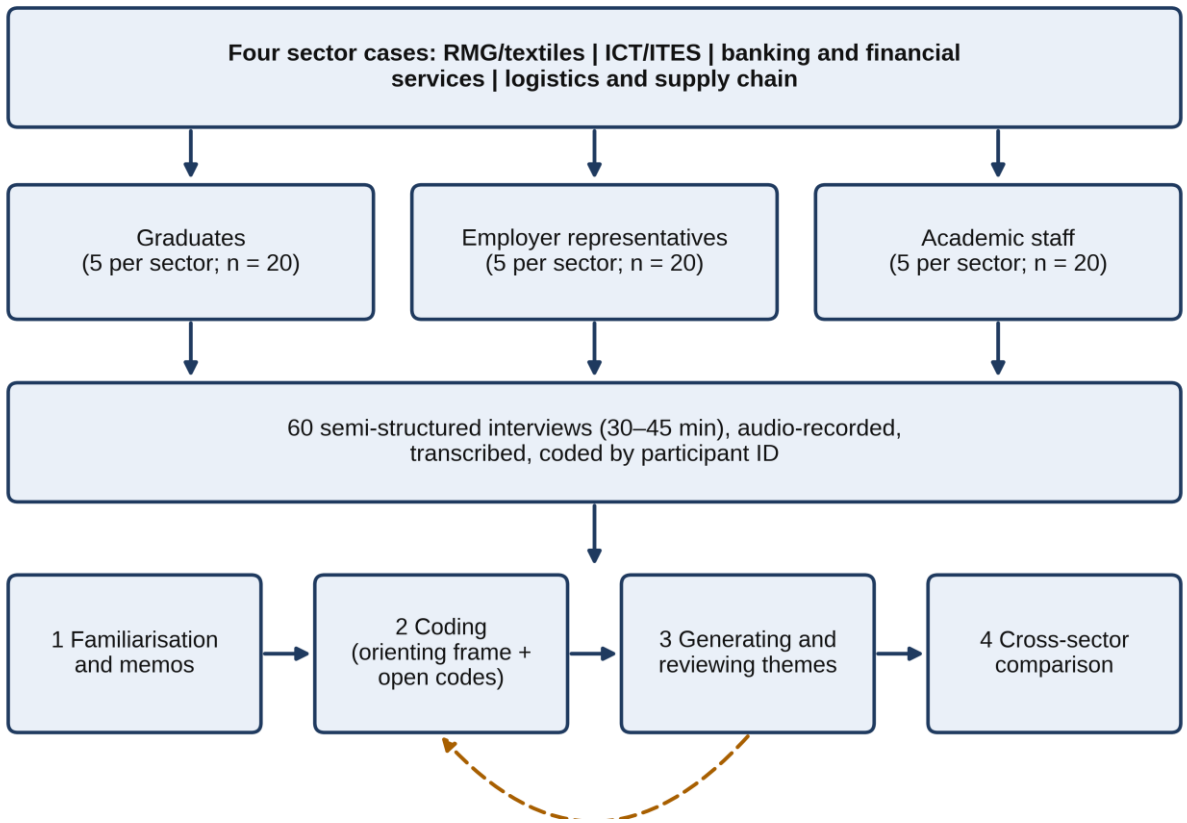


Fig. 2 Study design and analytic process. Sectors are comparison contexts; coding and theme review were recursive (dashed arrow), and reflexive memos and an audit trail were kept throughout

Documentary material was used only as context. Policy and sector documents cited in Section 2 informed the background, but job postings and curriculum documents were not

systematically sampled or analyzed, and no documentary findings are reported. The study therefore rests on interview data alone.

3.6 Reflexivity and positionality

The authors were university academics in a business studies department and approached the problem from a management and graduate-employability angle, not an engineering or computer science one. They may have been primed to interpret relatively technical descriptions of work by RMG and ICT/ITES participants more through notions of skills and curricula than of the technology itself. Their university status also meant they had pre-existing connections to the higher-education end of the sectors observed, and some graduate and academics may have known the authors or their department. To constrain social-desirability and hierarchical effects on participant answers, participants were told that all answers would be anonymised and not disclosed to their employer or institution, and interviewers sought illustrative rather than generalizable responses. The authors' reflexive memos reflected on how their positioning and expectations, including an expectation of AI prominence, shaped questioning and interpretation.

3.7 Ethical considerations

The Ethical Review Committee of State University of Bangladesh (SUB) approved the protocol, including all interview guides (serial number SUB/PH/H-ERC/2025/25, approval letter dated 12 November 2025). Data collection began in December 2025, after approval. All participants received an information sheet and gave informed consent, including consent to audio-recording, in writing or, for remote interviews, as recorded verbal consent. Participation was voluntary and could be withdrawn at any stage. Because sector-level studies can identify organizations, firms and universities are not named. Participants are identified only by alphanumeric codes (for example, RMG-G01), and potentially identifying details were generalized or omitted.

3.8 Use of generative AI

The authors used generative AI (Claude, Anthropic) while preparing this manuscript to help restructure and edit the text, suggest wording for some methodological descriptions (which the authors then checked against their own records and corrected), and prepare the layout of Fig. 3 from

the authors' content. The authors created Fig. 3 using plotting code, and it contains no AI-generated imagery. The authors did not use generative AI to collect, code, or analyze the interview data or to select quotations. The authors reviewed and verified all content, including the data and references, and take full responsibility for the manuscript. AI tools are not listed as authors.

4. Findings

4.1 Overview and evidence base

Based on the 60 interviews, four themes emerge (Fig. 3): (1) sector-specific technological change; (2) disciplinary knowledge as still necessary but no longer enough; (3) digital skills self-provision by graduates; and (4) institutional lag as a coordination problem, with diversification of programmes leading to uneven institutional readiness. The potential implications for graduate employability span all four and are discussed in section 4.6. The evidence base for this section is in Table 5.

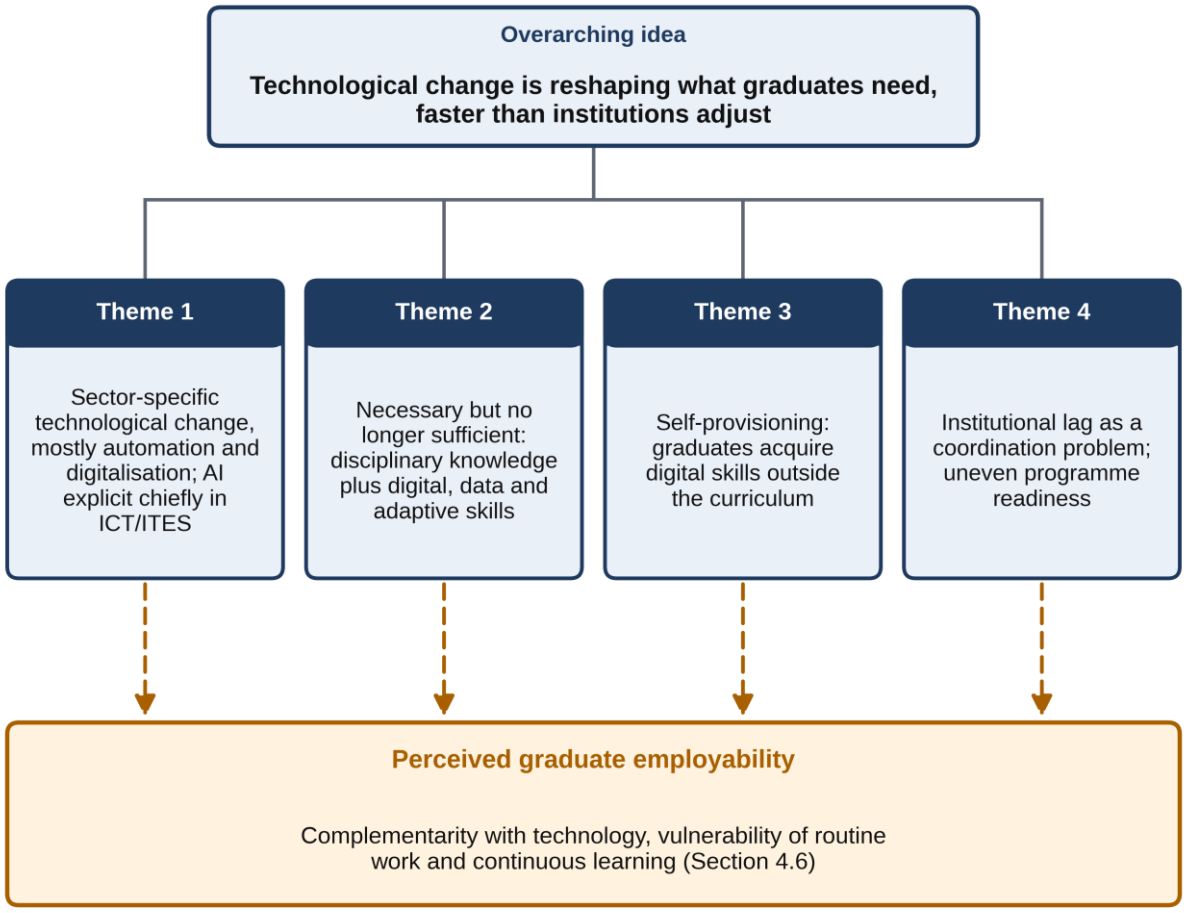


Fig. 3 Thematic map. Themes are parallel patterns developed from the data; dashed arrows show that all four bear on perceived graduate employability

Section 4 presents 31 extracts from 30 of the 60 participants. We included extracts to illustrate accounts repeated elsewhere in the analysis and to cover all four sectors and (if possible) all three stakeholder groups.10 Participants not quoted in section 4 are not included here. Ten ICT/ITES participants are quoted here, against six-seven from each of the other two sectors, so ICT/ITES voices are inflated in the extracts. An account is said to be repeated when it is illustrated here with extracts from two or more stakeholder groups from two or more sectors; no attempt is made to quantify all participants in the full corpus. Table 6 lists the sectors and stakeholder groups illustrated in each case.

Table 5 Extracts by sector and mention of AI

Sector	Participants quoted (of 15)	Extracts	Extracts naming AI explicitly	Technologies named in extracts
RMG/textiles	7	8	0	Automation, production data, software-based production systems, digital monitoring, "modern systems"
ICT/ITES	10	10	6	AI tools, AI topics, AI-assisted development
Banking and financial services	7	7	0	Automated processing, digital banking systems, analytics, digital processes
Logistics and supply chain	6	6	0	Technology and infrastructure, data-driven planning, operational systems
Total	30	31	6	

Note. Counts are of extracts reproduced in this paper, not of the full corpus. RMG-G04 is quoted twice. Analytic summaries record that banking participants linked AI to fraud detection, customer analytics and risk assessment, and logistics participants to AI-supported forecasting and optimisation; these accounts are not illustrated by an extract. Corpus-wide counts of participants who named AI explicitly were not compiled, so the paper makes no frequency claims about the full sample.

Table 6 Theme by sector and stakeholder group: extracts illustrating each theme

Theme	RMG/textiles	ICT/ITES	Banking	Logistics
1 Sector-specific change (Section 4.2)	E04, G05, A03	E05, G02, A02	E03, G02, A04	E02, G05, A02
2 Necessary but not sufficient (Section 4.3)	G04, E03	E02, E03, G03	E02	E04
3 Self-provisioning (Section 4.4)	G04	G04 (also G02)	G05	none quoted
4 Institutional lag (Section 4.5)	A03, A05	A02, A03, A04	A02, A04	E03, G03, A02
Perceived employability (Section 4.6)	E02	E01	G03	none quoted

Note. Codes give sector, group (G graduate, E employer representative, A academic) and participant number. Some extracts are cited in more than one section. Theme 3 rests on graduate accounts alone; employer and academic extracts do not address it.

4.2 Theme 1: Sector-specific technological change, mostly automation and digitalization

Participants in all four sectors described increasing exposure to digital technologies, but the technology they described, its speed and its consequences differed. Only in ICT/ITES did participants regularly name AI. Elsewhere they spoke of machines, software, digital banking and operational platforms. Sample context for each sector is in Online Resource 2 (which lists the number and type of organizations and universities represented in each sector).

4.2.1 RMG/textiles: automation as task restructuring

RMG participants described a gradual transformation of production work, not the wholesale replacement of occupations. Employers pointed to automated cutting systems, production-monitoring technologies, digital inventory management and computer-assisted manufacturing. One employer described the change in factory work from manual execution to technology-supported operation and supervision:

> *"Automation is reducing dependence on repetitive manual activities, but factories still need people who can operate machines, understand production data, and solve technical problems."* (RMG-E04)

Graduates said that textile knowledge remained important but had become insufficient without familiarity with production software and monitoring tools:

> *"Previously, knowing textile processes was enough for many positions, but now companies expect graduates to understand software-based production systems and digital monitoring tools."* (RMG-G05)

An academic linked this to curriculum timing:

> *"Industry technology changes faster than curriculum revision cycles. Universities need stronger industry collaboration to understand what skills students require after graduation."* (RMG-A03)

No RMG extract mentions AI. The accounts concern automation and digital production systems, and they concern graduate roles (operation, supervision and data interpretation), not the operative jobs to which the displacement estimates in Section 2.3 refer.

4.2.2 ICT/ITES: AI as augmentation of software work

ICT/ITES participants generally described AI as a tool that changes how work is done. They identified AI-assisted programming, analytics platforms and generative AI as embedded in workflows. Employers said that graduates' advantage now depends on how well they work with AI-enabled tools:

> *"AI is not replacing developers; it is changing the way developers work. A graduate who can use AI tools efficiently can complete tasks faster and produce better solutions."* (ICT-E05)

Graduates described learning these tools outside university:

> *"University gave me the foundation, but most AI tools and practical applications I learned through online courses and personal practice."* (ICT-G02)

Academics acknowledged the demand and located the difficulty in institutional capacity:

> *"The challenge is not recognizing the importance of AI; the challenge is continuously updating teaching materials, infrastructure, and faculty skills."* (ICT-A02)

The extracts do not distinguish software development from outsourcing or business-process work, which is likely to be more routine and more exposed to generative AI. This is a limit on what the ICT/ITES accounts can show.

4.2.3 Banking and financial services: process and role transformation

Banking participants described digital banking services, customer relationship systems, automated transaction processing, fraud detection and data-driven decisions. They described change in roles and rising demand for analytical and digital competence, not job elimination. An employer explained:

> *"Routine processing activities are becoming automated, but employees who can analyze information, manage digital systems, and understand customer data are becoming more valuable."* (BAN-E03)
>
> *"Banking graduates now need knowledge beyond finance. Understanding digital banking systems and analytics has become essential."* (BAN-G02)

An academic pointed to approval processes as the constraint:

> *"The banking industry has changed rapidly, but academic programs often require longer approval processes before introducing new courses."* (BAN-A04)

Participants in the analytic summaries linked AI to fraud detection, customer analytics and risk assessment, but the extracts above refer to automation, digital systems and analytics.

4.2.4 Logistics and supply chain: digitalisation constrained by infrastructure

Logistics participants identified digital tracking, warehouse management platforms, route optimisation and data-driven planning as areas of change. Compared with ICT and banking, they reported slower adoption because of infrastructure, investment and skills constraints:

> *"Technology adoption is increasing, but many organizations are still developing the infrastructure and workforce capability needed for advanced automation."* (LOG-E02)
>
> *"Supply chain jobs are becoming more data-driven. Knowing logistics processes is important, but companies also expect digital skills."* (LOG-G05)
>
> *"Students need exposure to real operational systems, not only theoretical supply chain concepts."* (LOG-A02)

4.3 Theme 2: Necessary but no longer sufficient

Across the four sectors, participants described disciplinary knowledge (textile processes, banking procedures, supply chain concepts, programming) as necessary but no longer enough. Recurring additions were digital literacy, data interpretation, familiarity with AI tools where relevant, adaptability and practical experience. Accounts came from employers and graduates in all four sectors; academics recognized the trend, but their extracts focus on constraints (Section 4.5).

Digital literacy as a baseline. Employers in ICT/ITES and banking described digital competence as expected of all staff, including those in traditional roles:

> *"Technical knowledge alone is not enough anymore. Graduates need to understand how technology is applied in real work situations."* (ICT-E02)
>
> *"Every employee does not need to become a programmer, but everyone needs to understand digital processes and technology-based services."* (BAN-E02)

AI tools as a differentiator, mainly in ICT/ITES. Only ICT/ITES extracts describe the ability to use AI tools as separating graduates:

> *"The difference between graduates is becoming their ability to use AI tools effectively. Those who learn these tools can complete tasks faster."* (ICT-G03)

Employers in other sectors did not expect graduates to become AI specialists, according to the analytic summaries; they valued understanding of how AI tools could support decisions.

Data interpretation and adaptability. A logistics employer stressed data interpretation, and an RMG graduate stressed learning ability:

> *"Modern supply chain decisions are increasingly based on data. Graduates who cannot interpret information will struggle to compete."* (LOG-E04)
>
> *"The technology used today may change within a few years. The most important skill is the ability to learn new systems quickly."* (RMG-G04)

Practical experience and job-readiness. Employers in ICT/ITES and RMG described a gap between conceptual knowledge and workplace application:

> *"Many graduates understand concepts, but they need practical exposure to know how these concepts work in professional settings."* (ICT-E03)
>
> *"Graduates understand theories, but companies need people who can immediately work with modern systems."* (RMG-E03)

Taken together, these extracts suggest that participants expect graduates to combine disciplinary depth with digital competence and practical readiness. Whether this amounts to a

general move from qualification-based to capability-based hiring cannot be established from these data, which include no hiring records.

4.4 Theme 3: Self-provisioning of digital skills

Graduates described acquiring digital and, in ICT/ITES, AI skills largely outside the curriculum, through online courses, professional communities and workplace exposure. This account was voiced by graduates in three of the four sectors (Table 6):

> *"Students cannot depend only on university courses anymore. Continuous self-learning has become necessary."* (ICT-G04)
>
> *"My university provided financial knowledge, but I learned most digital banking tools after joining the workplace."* (BAN-G05)
>
> *"We learned production principles, but many advanced systems used in factories were not covered deeply during our studies."* (RMG-G04)

ICT-G02 (Section 4.2.2) gave a similar account. These extracts describe a gap that graduates themselves had to close. Employer and academic extracts do not describe self-provisioning, and no logistics graduate is quoted on it, so this theme rests on graduate voices from three sectors.

4.5 Theme 4: Institutional lag as a coordination problem

Academics, employers and graduates all described curricula as changing more slowly than workplaces, but they located the problem differently. Employers emphasized graduates' job-readiness (Section 4.3). Academics emphasized structural constraints: slow curriculum approval, limited faculty training, limited access to updated technologies and weak industry collaboration. Graduates described what they did to compensate (Section 4.4).

> *"Updating curriculum is necessary, but universities need resources, trained faculty, and stronger industry partnerships to implement meaningful changes."* (ICT-A04)
>
> *"Faculty members also need continuous training because technology changes faster than traditional academic preparation."* (RMG-A05)

Employers and academics converged on weak information flow between industry and universities:

> *"Industries know what skills are needed, but this information does not always reach universities effectively."* (LOG-E03)

Access to tools was raised outside ICT. A logistics graduate said:

> *"Students may want to learn advanced technologies, but access to proper tools and practical environments is sometimes limited."* (LOG-G03)

Five factors emerged as shaping programme readiness, developed from the data: availability of technology-related courses; faculty capability and confidence; industry collaboration; access to digital infrastructure and tools; and opportunities for self-directed learning. Readiness appeared to vary by discipline. ICT/ITES academics described relatively greater integration of AI, programming and analytics:

> *"Computer-related disciplines have naturally incorporated AI topics, but other disciplines are still trying to understand how AI connects with their professional fields."* (ICT-A03)

This account is not uniform within the group, since ICT-A02 and ICT-A04 (above) describe continuing difficulty in updating content and faculty skills. Participants from RMG and logistics described technology content as supplementary or constrained by infrastructure. Banking academics described gradual incorporation of digital finance and analytics, with a further need for change:

> *"Finance education needs to move beyond traditional banking concepts and include analytics, fintech, and digital financial systems."* (BAN-A02)

We therefore treat readiness as varying by discipline, with ICT/ITES-related programmes described as more advanced, banking as intermediate, and RMG and logistics as more constrained (Table 7). These are the authors' interpretive ratings from the accounts, not measured levels.

4.6 Perceived implications for graduate employability

Participants' accounts concern what will matter for graduates, not employment outcomes. No extract concerns time to first job, pay, entry-level hiring practices or the use of AI in recruitment, and no participant raised soft skills, English proficiency, gender or socioeconomic background. Three views recurred.

Complementarity with technology. ICT/ITES employers said that graduates who work effectively with AI would do well:

> *"The graduates who succeed will not be those competing against AI, but those who know how to work effectively with AI."* (ICT-E01)

In banking, participants similarly valued employees who could use digital and analytical tools (BAN-E03, Section 4.2.3).

Vulnerability of routine work. RMG participants said that purely manual or repetitive roles faced pressure, and that demand was rising for technical supervision:

> *"People who only perform repetitive tasks face greater pressure because machines can increasingly handle those activities."* (RMG-E02)

Continuous learning. Learning after graduation was described as a condition of staying competitive:

> *"A degree helps you enter the profession, but continuous learning determines whether you can remain competitive."* (BAN-G03)

The extracts do not settle whether participants expected AI to eliminate graduate jobs. The nearest statements, from ICT/ITES employers (ICT-E01, ICT-E05), say that AI changes work and rewards those who use it. A general claim that participants rejected job elimination cannot be supported by these extracts. We return to this point in Section 5.6.

4.7 Cross-sector comparison

Table 7 arranges the sectors in a case-ordered meta-matrix. Ratings are the authors' interpretive judgments from the extracts and summaries, using the rubric in the table note. Symbols, not colors, encode levels, because "high" means different things for each column.

Table 7 Cross-sector meta-matrix: ratings, evidence pointers and rubric

Sector	AI named explicitly in accounts	Reported adoption of automation and digital tools	Reported programme readiness	Reported curriculum lag
RMG/textiles	○ Low (none in extracts)	◐ Moderate (E04, G05)	○ Low (A03, A05)	● High (G04, G05, E03, A03, A05)
ICT/ITES	● High (E05, G02, A02, G03, A03, E01)	● High (E05, A02)	● High (relative) (A03; contrast A02, A04)	● High (G02, G04, E03, A02, A04)
Banking and financial services	◐ Moderate (summaries only)	◐ Moderate (E03, G02)	◐ Moderate (A02, A04)	◐ Moderate (G05, A04, A02)
Logistics and supply chain	◐ Moderate (summaries only)	○ Low (E02)	○ Low (G03, A02)	● High (E03, G03, A02)

Note. Rubric. AI named explicitly: Low = not named in any reproduced extract or summary; Moderate = named in summaries only; High = named in extracts by more than one stakeholder group. Adoption: Low = accounts of adoption constrained by infrastructure or cost; Moderate = adoption of specific systems described; High = AI or digital tools described as embedded in routine work. Readiness: Low = technology content described as supplementary or infrastructure-constrained; Moderate = gradual incorporation; High = comparatively integrated content in core programmes. Curriculum lag: Moderate = described by two stakeholder groups; High = described by all three. Pointers are participant codes for each rating. Ratings were made independently by the two authors from the reproduced extracts and analytic summaries, with disagreements resolved by discussion, and they are ordinal, not measured.

Convergence. All four sectors identified increasing digital demand and some languishing curriculum, and all four sectors identified disciplinary knowledge as not being enough. Divergence. Technology ranged from automation and production lines in RMG to AI-enabled software applications in ICT/ITES, to digital banking systems and analytics, to infrastructure-limited digitalization in logistics. Readiness was higher in ICT/ITES-related courses than in RMG and logistics. All three stakeholder groups identified a reported curriculum lag in RMG, ICT/ITES, and logistics. All three stakeholder groups identified it in RMG, ICT/ITES, and logistics; only graduates and academics identified it in banking (no employer extract).

Reconciling the accounts with displacement estimates. The graduates in the interviews certainly did not lose their jobs, so it is not inconsistent with Section 2.3 that the press estimates a large movement of RMG workers. The press figures relate to numbers of RMG jobs; the discussions relate to perceptions. Once again, one should recall we are talking of perceptions relating to people working in or seeking to work in the sector (Section 5.6).

5. Discussion

5.1 Summary of the main findings

All four sectors reported that technological change was predominantly automation and digitalization, with the term 'AI' used overtly only in ICT/ITES. Disciplinary knowledge was essential but

insufficient; graduates were self-creators of gaps; curricula underperformed because institutional externalities neither universities nor employers alone could address. Preparedness seemed discipline-specific. The following sections address each research question, then explore anomalies, theoretical insights, and implications.

5.2 Automation, digitalization and AI (RQ1)

The key answer to RQ1 is that participants describe a shift that is not predominantly about AI. AI is named only in ICT/ITES extracts (Table 5). RMG accounts cover automated production and automation monitoring; banking accounts cover digital banking and analytics; logistics accounts cover tracking and planning. When AI is mentioned, it is present in summaries, not in extracts. Attributing the skill shift solely to AI oversteps the data, so this study cannot distinguish AI effects from broader digital transformation.

This pattern aligns loosely with the task-based literature. Automation of codifiable production and processing tasks in RMG and banking aligns with routine-task substitution (Autor et al., 2003); the ICT/ITES accounts align with the hypothesis that generative AI can move into non-routine cognitive work (Eloundou et al., 2024). The lack of task-level data and the inability to test displacement-reinstatement (Acemoglu & Restrepo, 2019) mean these extracts provide little evidence that new tasks or roles are emerging, except perhaps supervision and data interpretation in RMG. Logistical change and infrastructure constraints align with adoption-lag hypotheses (Rogers, 2003; Tornatzky & Fleischer, 1990); survey evidence from Bangladeshi supply chains is also consistent (Tasnim et al., 2023). Accounts of task change and skill upgrading in RMG broadly align with peer-reviewed evidence that automation in Bangladeshi apparel drove shifts in helper-level jobs (Hoque et al., 2022). However, the data concern graduate-level employment and cannot verify this.

5.3 Skill shift and the curriculum–industry gap (RQ2)

Thus, the accounts by participants of skills "necessary but no longer sufficient" point to what McGuinness et al. (2018) would term skill gaps, and those where earlier knowledge was called insufficient were partly due to skill obsolescence. The difference from the survey literature lies in the detail: the gap is described largely in terms of technology-specific competence and practical

preparedness, and academics give different reasons than unawareness, namely approval cycles, faculty skills, and industry links. This aligns with Bangladeshi work showing that curricular reform alone will not close the gap (Hasan et al., 2024) and that practical work helps (Hossain & Arefin, 2025). This implies that technology is resetting the gap, so no single iteration of reform will close it; the study does not show it has widened because it lacks a baseline. Employers, academics, and graduates framed the gap differently: employers saw it as preparation for work, academics saw it as structural limitations, and graduates saw it as something they needed to do themselves. All three framings reflect a common coordination problem: each perceived the missing element as located with the other. The theme of self-provisioning leaves open the important but unanswerable question about whether graduates with more financial and technological access, network access and time for online study can adapt better than other graduates.

5.4 Programme readiness, graduates' literacy and employability (RQ3)

RQ3 asked about the relationship between stakeholders' readiness and graduates' digital and AI literacy in relation to employability prospects. The accounts portray readiness as discipline-dependent, more integrated in ICT/ITES-related curricula and less constrained in RMG and logistics curricula (see Table 7). Read through the TOE framework (Tornatzky & Fleischer, 1990), all five readiness factors fall under technological conditions (infrastructure, tools), organisational conditions (courses, faculty members), and environmental conditions (industry linkages, features of industry-enabling self-regulation). Read through absorptive capacity (Cohen & Levinthal, 1990), faculty members with no relevant prior knowledge are less capable of importing and teaching new knowledge. Participants' descriptions of national-level support and university practices are also consistent with the notion that policies are not implemented programmatically (ICT Division 2023; IREX and Development Gateway 2026).

The assertion that readiness moderates exposure is not made. The comparison was by sectors, not programmes with different readiness within a sector, and no outcome data were collected. The limited evidence available supports this: the extract participants link graduates' readiness to what programmes offer and describe readiness as uneven across disciplines. Two principles are therefore proposed for

testing: programme readiness determines when the skill shift becomes a widening curriculum-industry divide (P1); and graduates' own digital and AI literacy determines how that divide appears as employability risk (P2). Two additional points are made below that hamper any more extensive interpretation: firstly, ICT/ITES graduates were not identified as most vulnerable, but the extracts do not indicate participants comparing vulnerability between sectors, and secondly, accounts still indicated significant lag (ICT-A02, ICT-A04), so higher relative readiness did not mean high absolute readiness.

5.5 Convergence and divergence across sectors (RQ4)

All four sectors agreed on the direction of change (more digital competence expected, some lag in curriculum), but differed on the technology, speed of uptake and reported readiness (see Table 7). This reinforces the argument for considering multiple trajectories in Bangladesh, rather than a single national average, which is especially pertinent for cross-country estimates that must necessarily combine sectors (Gmyrek et al., 2026; World Bank 2026). At the perception level, we adjusted the labels assigned to each sector (see Table 2) rather than validated them: RMG was characterized in terms of task change (no AI), ICT/ITES as AI-augmented, and none of the sectors fit squarely as an example of graduate displacement.

5.6 Unexpected results and alternative explanations

The most striking finding is the absence of graduate job loss in the participants' reports, even within RMG, where press and industry are collectively bemoaning mass displacement. Several potential, non-mutually exclusive explanations are possible but cannot be distinguished here. (a) The participants reference occupations, not education levels, so that graduate employment may be affected secondarily and in the long run. (b) Employers and academics are interested in the story of reskilling, not replacement; employed, job-seeking graduates presumably form the subsequent 'cohort' that entered the sector after 2003, whereas those who have exited or been displaced cannot be sampled. (c) The participants' response bias and the 'stimuli' posed by the interview questions may have elicited 'correct' technology answers. (d) Diffusion delays may delay observable displacement effects in graduate occupations, and the sample excludes informal-sector mechanisms. (e) Other factors,

liberalization-induced LDC graduation and political change, may be more influential on employment between 2004-14 (Section 2.3). These explanations reaffirm that the report's findings reflect changes in skills, not changes in employment.

The paper also fails to consider a handful of other factors that the Bangladeshi guides consider important. The employer guide included a question about whether the employer preferred foreign workers; for reasons beyond the scope of this paper, this analysis does not include that data. Socioeconomic constraints, the internet-reliance of English and soft skills were not discussed and were not included in the guides. The WDR digital-divide explanation could not be explored as connectivity statistics were not collected.

5.7 Theoretical contribution

The contribution is limited and specific. First, using a developing-country case, this paper documents that four sectors' human capital developers mostly talk about automation and digitalization, and that nearly all talk of AI is in one sector. This should discourage any claim that changes in demanded skills are mostly attributable to AI without evidence, and it provides the skills-mismatch literature (Hossain & Arefin, 2025) with a sector-differentiated qualitative account of what the mismatch consists of. Second, it attempts to give structure to the mismatch: programme readiness and graduates' AI literacy are posited as two conditioning, rather than intervening, variables. This is an analytical hypothesis, not an empirically tested moderator; it aligns more with adoption-capacity models (Cohen & Levinthal, 1999; Rogers, 2003; Tornatzky & Fleischer, 1990) and less directly with task-based models, which account for task selection rather than adoption capacity. Figure 4 highlights the links for which these hypotheses are made with solid arrowheads; the

exposure-to-skill-demand link was not tested with respect to any, and has no arrowheads.

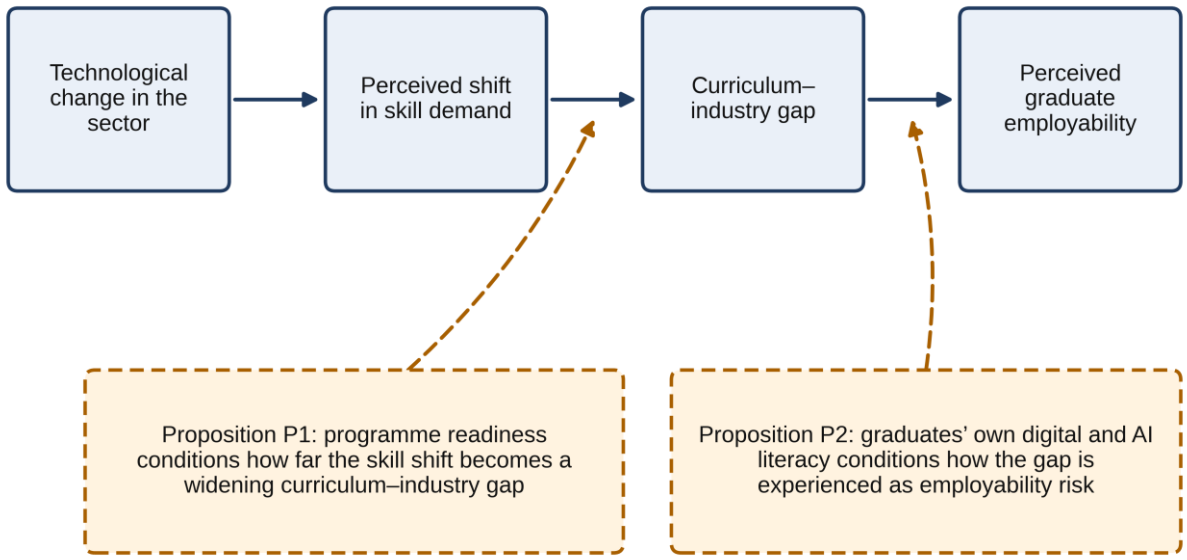


Fig. 4 Analytic propositions for future testing. Dashed arrows land on the links they are proposed to condition; they are not demonstrated moderating effects, and the link from technological change to skill demand was not examined for conditioning

5.8 Implications for practice and policy

Table 8 links each recommendation to the finding that supports it, the actors who could act, and a time horizon. Recommendations follow from participants' accounts; where a suggestion rests on external evidence, this is stated.

Table 8 Recommendations, supporting findings, responsible actors and time horizon

Recommendation	Supporting finding	Actors	Horizon
Shorten and simplify approval of technology-related course changes	Slow approval cited as a constraint (RMG-A03, BAN-A04, ICT-A04)	University academic councils and IQACs; UGC guidance	1–2 years
Fund faculty development in industry technologies	Faculty capability as a readiness factor (RMG-A05, ICT-A02)	Universities; IQAC and quality-enhancement programmes; industry partners	1–3 years
Build structured employer–university collaboration: advisory input, projects, internships	Information about needs "does not reach universities" (LOG-E03); need for exposure to real systems (LOG-A02, ICT-A04)	BGMEA, BASIS, banks and logistics associations with university departments	1–2 years
Embed applied digital and data content in core programmes, especially outside ICT	Technology content described as supplementary in RMG, banking and logistics (Section 4.5; BAN-G05, RMG-G04)	Department curriculum committees	2–3 years
Improve access to software, labs and operational systems in RMG and logistics programmes	Limited access to tools (LOG-G03, LOG-A02)	Universities; industry licence and equipment partnerships	2–4 years
Recognise short, verified online learning in ways employers accept	Graduates learned tools online or on the job (ICT-G02, ICT-G04, BAN-G03); micro-credentials also viewed as a partial remedy in other Bangladeshi work (Sarker et al. 2026)	NSDA and BNQF-aligned providers; employers	2–3 years

Note. The last recommendation rests partly on external evidence and should be piloted before scaling.

The findings give little support for a single national instrument. Sector-specific approaches, targeted at programmes and departments where readiness is described as lowest, fit the accounts better than uniform ones. The draft National AI Policy 2026–2030 (ICT Division 2026) and Smart Bangladesh 2041 (ICT Division 2023) could be complemented by such programme-level measures.

6. Limitations and Future Research

Several limitations temper how far the results can be generalized. The data reflect self-reported perceptions collected at one point during an unusual conjuncture of rapid innovation, with retrospective assessments of the previous two to three years and no pretest comparisons. Answers to some questions may have been contaminated by social desirability or presupposition of some prompts. The five cells preclude within-sector inference, and purposive and snowball sampling likely produced an unrepresentative selection of organizations and higher institutions in Dhaka, or those willing to participate; gatekeepers in sector associations may have influenced recruitment decisions. The interviewer translated and transcribed Bangla responses as needed (Section 3.4), and lightly paraphrased quotations. The authors double-coded only 10 of 60 transcripts. Records of refusals and the number of re-referrals are unavailable, so the authors cannot estimate the effects of self-selection. The authors report no member-checking of the analyses. The report includes no negative-case analysis, so the extracts illustrate only common themes; it quotes 30 of 60 respondents, and ICT/ITES is overrepresented among them.

Other voices are absent: displaced (former) employees and other workers; graduates who have left the sector or are unemployed; policymakers, regulators, TVET providers, trade unions, and students. Employers and academics might favor a reskilling argument, and graduate survivors may explain the absence of displacement. The study did not address soft skills, English language skills, gender, or sociodemographic factors. The study examined no documentary evidence, so only anecdotal evidence supports the assertion that requirements have changed.

Additional potential directions for research on these questions could include: Job-posting and curriculum documents as evidence of requirement changes; Employer panel survey and graduate

tracer studies as evidence of outcomes; Survey/mixed methods study as evidence against the propositions P1 and P2 empirically tested for programme, different levels of sector readiness; Follow-up interview research with policymakers and officers in relevant sector associations, displaced workers and graduates not engaged with the industry by gender and socioeconomic position; Longitudinal design to assess whether the trajectories identified in the sector here consolidate as use of AI emerges.

7. Conclusion

This paper examined the narratives of 60 graduates, employer representatives and academics across four Bangladeshi sectors. Attendees' narratives centred on automation and digitalization, with explicit references to AI only in ICT/ITES. Attendees described skills as discipline-specific knowledge that was necessary but not sufficient, with graduates themselves narrowing skill gaps and curricula out of date due to institutional path dependencies that require concerted institutional action. Attendees' narratives suggested discipline-specific differences in readiness, which I offer as a proposition to test, not as a tested mechanism. These findings refer to perceived skill change, not employment impacts, and do not conflict with estimates of operative displacement in RMG.

For universities, employers, and sector bodies, the bottom line is that recruitment or a single round of curriculum reform is unlikely to bridge the gap. The reports point to faster approval processes, faculty development, staff and employer engagement structures, and easier access to tools, targeted at the programmes where readiness is rated lowest.

Statements and Declarations

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Ethics approval. This study was performed in line with the principles of the Declaration of Helsinki. Approval was granted by the Ethical Review Committee of State University of

Bangladesh (SUB) (serial number SUB/PH/H-ERC/2025/25; approval letter dated 12 November 2025). Data collection began in December 2025, after approval.

Consent to participate. Informed consent was obtained from all individual participants included in the study, including consent to audio-recording, in writing or as recorded verbal consent for remote interviews. Confidentiality of responses was maintained throughout the study.

Consent for publication. Not applicable. Participants are identified only by anonymised codes, and firms and universities are not named.

Data availability. The interview transcripts and the case database contain information that could identify participants and organizations, and participants did not consent to public sharing, so they cannot be made publicly available. Further de-identified extracts are available from the corresponding author on reasonable request, subject to ethics approval and the conditions of participant consent.

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