ARL-TR-9432 ● APR 2022

DEVCOM ARMY RESEARCH LABORATORY

How to Prepare for Rapidly Evolving Technology: Focus on Adaptability

by Kimberly A Pollard, Benjamin T Files, Ashley H Oiknine, and Bianca Dalangin

NOTICES

Disclaimers

ARL-TR-9432 ● APR 2022

How to Prepare for Rapidly Evolving Technology: Focus on Adaptability

Kimberly A Pollard and Benjamin T Files
DEVCOM Army Research Laboratory

Ashley H Oiknine and Bianca Dalangin
DCS Corporation

REPORT DOCUMENTATION PAGE	*Form Approved* *OMB No. 0704-0188*

1. REPORT DATE *(DD-MM-YYYY)*	2. REPORT TYPE	3. DATES COVERED (From - To)
April 2022	Technical Report	2018–2022

4. TITLE AND SUBTITLE

How to Prepare for Rapidly Evolving Technology: Focus on Adaptability

5a. CONTRACT NUMBER

5b. GRANT NUMBER

5c. PROGRAM ELEMENT NUMBER

6. AUTHOR(S)

Kimberly A Pollard, Benjamin T Files, Ashley H Oiknine, and Bianca Dalangin

5d. PROJECT NUMBER

5e. TASK NUMBER

5f. WORK UNIT NUMBER

7. PERFORMING ORGANIZATION NAME(S) AND ADDRESS(ES)

DEVCOM Army Research Laboratory
ATTN: FCDD-RLH-FC
Aberdeen Proving Ground, MD 21005

8. PERFORMING ORGANIZATION REPORT NUMBER

ARL-TR-9432

9. SPONSORING/MONITORING AGENCY NAME(S) AND ADDRESS(ES)

10. SPONSOR/MONITOR'S ACRONYM(S)

11. SPONSOR/MONITOR'S REPORT NUMBER(S)

12. DISTRIBUTION/AVAILABILITY STATEMENT

Approved for public release: distribution unlimited.

13. SUPPLEMENTARY NOTES

ORCID IDs: Kimberly A Pollard, 0000-0002-5849-1987; Benjamin T Files, 0000-0002-1141-7886

14. ABSTRACT

Technology is advancing at a rapid and ever-accelerating pace, requiring human users to continually adapt to new interfaces, systems, and capabilities. Some emerging technologies such as advanced artificial intelligence (AI) can even update their capabilities and behaviors in real time, requiring human adaptation on the fly. How can we prepare users to adapt to these changes and, indeed, prepare them to work with future technologies that have not yet been invented or even imagined? The speed and unpredictability of technological evolution suggests a generalized approach is warranted. Training and selecting personnel for adaptability itself will yield more flexible, rapid, and robust results than relying solely on a reactive program of training on each specific technology as it comes out. In this report, we lay out the case for a focus on adaptability. We then outline a research approach that can 1) enable the identification and testing of fundamental skills and other characteristics associated with generalized tech adaptability, 2) allow personnel selection and team construction based on these characteristics, and 3) identify training and other interventions that can enhance these key generalizable characteristics. Effective use of these methods will result in users with enhanced ability to adapt to new, emerging, unknown, changing, and even not-yet-invented technologies.

15. SUBJECT TERMS

human-machine interaction, rapid adaptation, generalizable skills, testbeds, training, individual differences

16. SECURITY CLASSIFICATION OF:			17. LIMITATION OF ABSTRACT	18. NUMBER OF PAGES	19a. NAME OF RESPONSIBLE PERSON
					Kimberly A Pollard
a. REPORT	b. ABSTRACT	c. THIS PAGE	UU	19	19b. TELEPHONE NUMBER (Include area code)
Unclassified	Unclassified	Unclassified			(310) 574-5709

Standard Form 298 (Rev. 8/98)
Prescribed by ANSI Std. Z39.18

Contents

List of Figures

1. Introduction and Background

Adapting to technology is becoming more difficult as technology advances more and more quickly. As technology advances, human behavior and cognition change to best make use of the new technologies. For example, remembering facts and procedures often used to be the responsibility of the individual human brain. Paper documents provided an additional option for slow-access information retrieval when necessary, but for a quick answer, human memorization was key. With the dawn of the Internet and search engines, humans have offloaded much of this effort to machines. We now spend our mental energy less on knowing *what the answer is* and more on *how to quickly find and access the answer*. It is no longer about what you know; it is about whether you know Google-fu.[*] This represents a significant transformation in human thinking—an adaptation to a new human–technology landscape. As a result, this collective human–machine system can answer orders of magnitude more questions in a fraction of the time versus what a system or a human could alone. Achieving these leaps does not just require good technology, it requires that humans *learn* and *adapt to* that technology.

Technology adaptation has been with us since the earliest days of human ingenuity. The invention of the wheel fundamentally changed the way we think about movement and weight. The invention of the car fundamentally changed the way we think about distance, time, and work. Those who could adapt and think in these new ways were able to reap incredible benefits. Those who could not were left behind. Just as humans had to fundamentally adapt their thinking to wheels, the automobile, and the computer, we must soon adapt to advanced artificial intelligence (AI), fully autonomous systems, neuroprosthetics, brain–machine interfaces, and other technologies that we cannot even imagine yet. We will need to adapt to maximize the benefits and stay ahead in a competitive world.

However, adaptation is becoming more difficult because technology is advancing faster than ever before. Consider how much time an ancient farmer had to adapt to a new design of hand plow versus how much time a modern Soldier has to adapt to a new operating system interface for an AI-enabled, cutting-edge unmanned vehicle. The risk of taking too long to adapt clearly differs as well. Some modern intelligent technologies even react to new data and change their behavior in real time, requiring users to adapt on the fly. The system you are using may be more advanced than it was just 5 min before. The rate of technological evolution is faster

[*] *Google-Fu* is a term referencing a person's skill in using search engines to efficiently find desired information.

than ever, it is accelerating, and breakthroughs are becoming more unpredictable (Cronin 2020). How can we keep up?

2. Traditional Methods

The traditional method of adaptation is for humans to learn each new technology as we go. This can be self-taught and exploratory, or it can involve targeted training designed for specific technologies. For example, we might get a new cell phone and then figure out how to use its functions one by one. It might take months or even years before we make full use of the phone's potential. By that time, there is a new phone model out with different controls that now must be learned.

When the new technology is job-related or highly specialized, leisurely learning-as-we-go may not be a viable option. In this case, specialized training programs step in. Seminars, training simulations, videos, manuals, and course curricula are produced, each specifically designed to aid a user in adapting to a single new piece of software, a particular new gadget, or one new information system. The next new piece of technology then starts this cycle again, spawning a new wave of training products geared to train users on this one specific new item. An approach like this is piecemeal and reactive; it will always lag significantly behind the technology it endeavors to train. Despite this lag, these methods have been generally effective for most of human history. The benefits of new technologies often justify the extensive training time investment. This has been true even in fast-paced competitive domains (e.g., if a new technology is 5 years ahead of your competitor's, you could spend years in training to use it and still come out ahead). However, as the pace of technological advancement accelerates and becomes increasingly globalized, this reactive approach will not be fast enough to keep up. This is particularly of concern in high-stakes, fast-paced fields where falling behind could mean losing a customer, losing a patient, or losing a battle.

One alternative would be to anticipate future technologies, identify task domains in which they are relevant, and pretrain users before the specific technology arrives. This could be achieved in various simulation contexts. However, prognosticating about future technology can be error prone, and simulations may be difficult to generate depending on the capabilities needed. Pretraining for specific systems is difficult for technologies that do not yet exist, but it is virtually impossible for technologies we have not yet imagined. What can we do?

3. Adaptability is Key

The common thread linking past and present examples of technology adaptation is the users' ability to flexibly change their fundamental ways of thinking. Adaptability is the core of what we need, so why not train adaptability itself? We should train people on fundamental, generalizable skills that will help them adapt to new technologies regardless of what forms those technologies take.

We can start by examining what makes some people more proficient than others at learning new technologies. This may seem like a hard thing to define, but research from different disciplines has identified some skills that improve a person's ability to learn new technologies.

4. Fundamental Skills and Characteristics

For example, people with high levels of openness to experience, creativity, and flexible thinking have been found to display more technological proficiency, use more of a given technology's capabilities, and are quicker and more accurate when accessing information with technology (Kim and Jeong 2015; Barak 2018; Hölscher and Strube 2000). Distraction and distractibility are consistently a hindrance to tech adaptation (Ford et al. 2001; Lei et al. 2015), as are anxiety, fear of failure, or fear of the technology (Ford et al. 2001). Graph literacy (i.e., the ability to interpret charts and data visualizations) and the ability to process uncertain information can help people employ more effective human–technology thinking with a variety of computer and information systems (Padilla et al. 2018). Spatial skills correlate with improved human–autonomy interaction (Chen and Barnes 2014) and may facilitate perspective-taking. In general, a better understanding of how the technology or AI agent takes in information, stores it, and processes it can greatly improve interaction with the technology and enhance performance. We might consider this type of understanding to be analogous to perspective-taking or theory of mind employed to understand other humans and work with them more effectively (Cuzzolin et al. 2020). Crouser and Chang (2012) suggest additional human skills and characteristics that may affect human–computer interactions to facilitate greater collaborative problem solving. These include visual perception, audiolinguistic ability, visuospatial thinking, and creativity. Shared mental models can facilitate human–technology teaming (Nikolaidis and Shah 2012), and humans' mental models of systems evolve with use (Westbrook 2006; Han et al. 2020). Many other promising candidates remain to be identified and tested and may include skills such as numeracy (i.e., facility with math and numbers), pattern recognition, field dependence/independence (i.e., tendency to see broader patterns versus details), and trust calibration.

Figure 1 summarizes some of these skills and characteristics as well as how they might fill the anticipated needs of technology adaptation. Many of these skills and characteristics have standardized or validated metrics to measure them (e.g., personality questionnaires, spatial ability tests), but others do not. Assessing some of these skills and characteristics will thus require the development of novel testbeds and measurement tools.

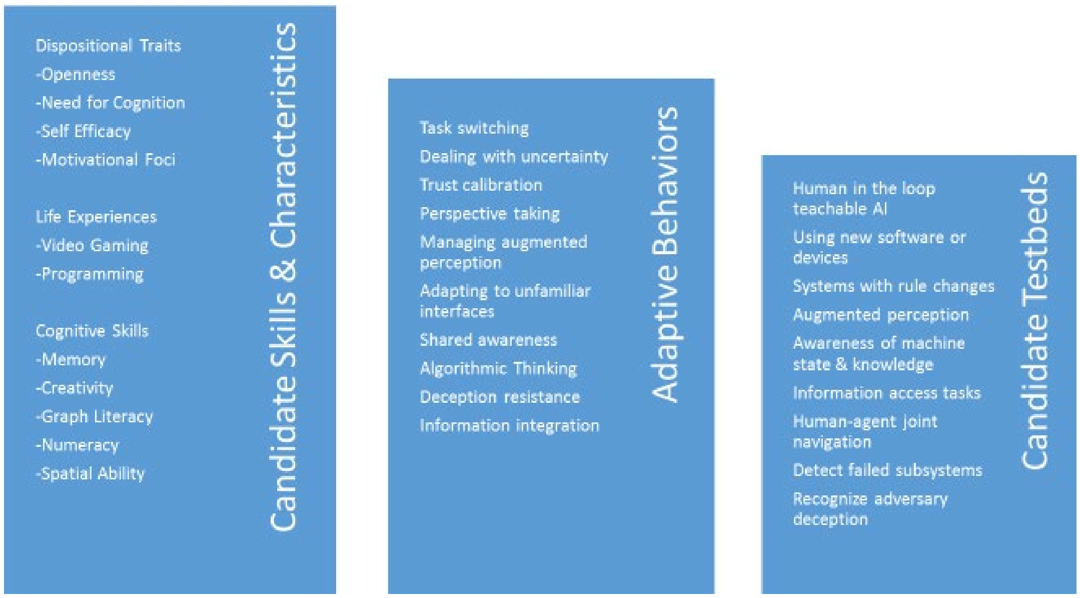

Fig. 1 Column 1 lists examples of candidate skills and characteristics that we believe may fundamentally contribute to a person's ability to adapt to technology. Column 2 lists specific adaptive behaviors—which may be thought of as higher order composite skills—that we believe may be critical for rapid adaptation to many technologies, including anticipated future technologies. Column 3 lists a broad range of technological tasks that target different composite skills, which when incorporated into testbeds could be used to assess technology adaptation performance.

5. Improving These Abilities

Creativity, openness, flexible thinking, spatial ability, perspective taking, and so forth—these cognitive skills may at first glance seem more like immutable personality traits than trainable skills. However, a broad body of literature suggests that many of these core cognitive skills and characteristics can, in fact, be trained or influenced. This is counter to the popular outlook that such skills are set in stone or "just something you're born with." Creativity, spatial skills, numeracy, theory of mind, and even some aspects of personality can be altered, temporarily or permanently, to influence behavior (Uttal et al. 2013; Newcombe and Shipley 2015). For example, a variety of interventions have been demonstrated to enhance creativity and openness to experience. These include nostalgia priming (van Tilburg et al. 2015), semantic priming with achievement words (Dennis et al. 2013), growth mindset induction (Porter and Schumann 2018), and meditation (Ding et al. 2014). Theory of mind capability development is typically studied in young children, but evidence indicates that training can improve theory of mind skills in those outside the critical development window (Goldstein and Winner 2012). Openness and theory of mind capabilities may be enhanced by mindfulness, a skill that can also be trained (Kaviani and Hatami 2016). Perspective-taking ability has been enhanced using imitation–inhibition training (Santiesteban et al. 2012) and social false belief task training (Ereira et al. 2020).

Knowing about these fundamental cognitive skills and characteristics is valuable for personnel selection and team formation. It can inform decisions on which person to assign to which group or to which given technology-based task to achieve the best results. Furthermore, many of these characteristics and skills can be influenced by training or other interventions. In short, we have the means to turn the tech-struggler into a confident, rapid adopter. And we have the means to make the rapid adopter even more adept.

6. A Place for Adaptability Training

Training these core adaptability skills should enable users to rapidly adapt to emerging and far future technologies even without explicit training on the actual system. This should lessen the need for traditional system-specific forms of training and should make the learning process faster when specific training does occur.

Perhaps most importantly, such training is uniquely proactive and future proof. Because these fundamental cognitive skills enhance adaptation itself, users should more readily attain proficiency with any new technology, regardless of its exact nature. Training fundamental skills eliminates the need to prognosticate about future technological designs, and it does not require playing catch-up with written manuals and curricula.

This is not to say that we should abandon system-specific training. On the contrary, existing training can be highly effective, albeit sometimes slower than desired. The training of fundamental adaptability skills can be embedded into existing curricula and/or performed using existing simulators and existing training technology. Spatial skills or perspective-taking training, for example, can fit easily into existing virtual-environment or simulated-interface training systems. System-specific focused training can still be conducted as needed, but we should be able to reduce this need and speed up focused training once users have enhanced adaptability skills.

7. Conclusion: Making It Work

Ensuring users can rapidly adapt to new and changing technologies will require several steps. First, we must evaluate candidate skills and characteristics (pulled from literature, prior work, and theory) against a battery of human–technology adaptation tasks. This will help to determine which skills are most generalizable and transferrable. Second, we must identify which skills or characteristics can be affected by training or other interventions and develop effective ways to enhance these skills. Third, we must demonstrate that we can improve a person's adaptation to a range of new technologies by training them in one or more of these skills.

For the first step (i.e., evaluate candidate skills for generalizability), we must consider that the list of candidate skills and characteristics is long, and these must be tested against a broad selection of human–technology tasks to determine which skills/characteristics are relevant to the broadest range of human–technology interaction contexts. These tests will also need to involve a broad enough sample of study participants so that we can capture the variability in these characteristics. The resulting list of key skills and characteristics can be harnessed straightaway for use in workforce selection and team composition decisions. For the second step (i.e., identify effective training interventions), we will need to draw from lessons learned in the training, simulation, and learning research fields. We will need to explore a range of options available in modern training technologies, likely including individualized adaptive training, gamified or other motivational elements, immersive virtual or augmented reality training, and other simulations. Wearables, neurostimulation, or pharmacological interventions could also be considered. For the third step (i.e., demonstrate successful transfer to a new human–technology context), study participants will need to be challenged with a human–technology task that is unfamiliar to them to assess how quickly they adapt as a result of their training. This step requires identifying existing testbeds or developing new ones to assess a user's adaptation to technology. The testbeds could employ existing technologies that are specialized, obscure, or highly advanced and thus not popularly used. Examples could be as intensive as having a participant interact with a complex machine-learning algorithm that updates its own behavior in real time, or they could be as straightforward as sitting a person in front of a commercial-off-the-shelf software package or device they have never used before and observing how quickly they adapt to working with it. Testbeds could also include simulations of advanced technologies that are not yet in existence. These can be simulated using Wizard of Oz methods[*] or using machine algorithms that appear to have advanced

[*] In Wizard of Oz methodology, a concealed human confederate guides the behavior of the simulated technology, unbeknownst to the user who believes they are interacting with a machine.

intelligence but are actually following a predefined script, rail movement, and so on. Figure 2 diagrams these three critical research steps. Appendix A summarizes this research approach and rationale.

This work will require pulling together knowledge and approaches from diverse fields of study. The efforts will pay off in allowing users to adopt new technologies more readily, enjoy speedier times to proficiency, and enable more extensive use of each human–technology system's capabilities. By enhancing adaptability itself, we can enable users to adapt rapidly to whatever new technology they need—even emerging, unknown, and as-yet-unimagined technologies.

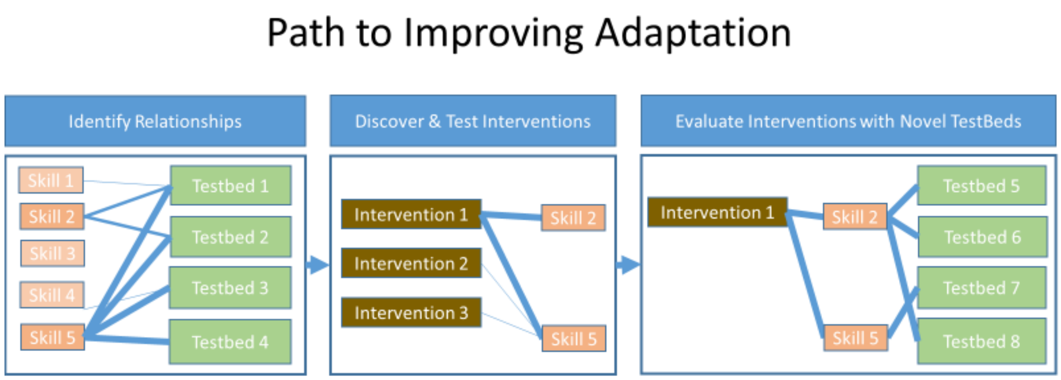

Fig. 2 Three key research steps for adaptation training: First, candidate skills and characteristics are tested against a broad array of technologies in different testbeds. Second, a down-selected pool of skills and characteristics is tested as the target of training or other intervention techniques. Third, successful interventions are employed to determine whether they improve adaption to a novel set of technology testbeds via enhancing the targeted skills/characteristics.

8. References

Barak M. Are digital natives open to change? Examining flexible thinking and resistance to change. Comput Educ. 2018;121:115–123. https://doi.org/10.1016/j.compedu.2018.01.016.

Chen JYC, Barnes MJ. Human–agent teaming for multirobot control: a review of human factors issues. IEEE Trans Hum Mach Sys. 2014;44(1):13–29. https://doi.org/10.1109/THMS.2013.2293535.

Cronin AK. Technology and strategic surprise: adapting to an era of open innovation. Parameters. 2020;50(3):71–84.

Crouser RJ, Chang R. An affordance-based framework for human computation and human-computer collaboration. IEEE Trans Vis Comput Graph. 2012;18(12):2859–2868. https://doi.org/10.1109/TVCG.2012.195.

Cuzzolin F, Morelli A, Cîrstea B, Sahakian BJ. Knowing me, knowing you: Theory of mind in AI. Psychol Med. 2020;50(7):1057–1061. https://doi.org/10.1017/S0033291720000835.

Dennis AR, Minas RK, Bhagwatwar AP. Sparking creativity: improving electronic brainstorming with individual cognitive priming. J Manag Inf Syst. 2013;29(4):195–216. https://doi.org/10.2753/MIS0742-1222290407.

Ding X, Tang Y-Y, Tang R, Posner MI. Improving creativity performance by short-term meditation. Behav Brain Funct. 2014;10(1):9. https://doi.org/10.1186/1744-9081-10-9.

Ereira S, Hauser TU, Moran R, Story GW, Dolan RJ, Kurth-Nelson Z. Social training reconfigures prediction errors to shape self-other boundaries. Nat Commun. 2020;11(1):1–14. https://doi.org/10.1038/s41467-020-16856-8.

Ford N, Miller D, Moss N. The role of individual differences in internet searching: an empirical study. J Am Soc Inf Sci Technol. 2001;52(12):1049–1066.

Goldstein TR, Winner E. Enhancing empathy and theory of mind. J Cogn Devel. 2012;13(1):19–37. https://doi.org/10.1080/15248372.2011.573514.

Han Z, Hansen P, Xu H, Luo R. Examining the classification and evolution of novice users' mental models of an academic database in the search task completion process. J Inf Sci. 2020;46(2):205–225. https://doi.org/10.1177/0165551519828621.

Hölscher C, Strube G. Web search behavior of Internet experts and newbies. Comput Netw. 2000;33(1–6):337–346. https://doi.org/10.1016/S1389-1286(00)00031-1.

Kaviani H, Hatami N. Link between mindfulness and personality-related factors including empathy, theory of mind, openness, pro-social behaviour and suggestibility. Clinical Depression. 2016;02(04). https://doi.org/10.4172/2572-0791.1000119.

Kim Y, Jeong JS. Personality predictors for the use of multiple internet functions. Internet Res. 2015;25(3):399–415. https://doi.org/10.1108/IntR-11-2013-0250.

Lei P-L, Sun C-T, Lin SSJ, Huang T-K. Effect of metacognitive strategies and verbal-imagery cognitive style on biology-based video search and learning performance. Comput Educ. 2015;87:326–339. https://doi.org/10.1016/j.compedu.2015.07.004.

Newcombe NS, Shipley TF. Thinking about spatial thinking: new typology, new assessments. In: Gero JS, editor. Studying visual and spatial reasoning for design creativity. Springer Netherlands; 2015. p. 179–192. https://doi.org/10.1007/978-94-017-9297-4_10.

Nikolaidis S, Shah J. Human-robot teaming using shared mental models. Proceedings of ACM/IEEE HRI; 2012. 1–6.

Padilla LM, Creem-Regehr SH, Hegarty M, Stefanucci JK. Decision making with visualizations: A cognitive framework across disciplines. Cogn Res Princ Implic. 2018;3(1):29. https://doi.org/10.1186/s41235-018-0120-9.

Porter T, Schumann K. Intellectual humility and openness to the opposing view. Self Identity. 2018;17(2):139–162. https://doi.org/10.1080/15298868.2017.1361861.

Santiesteban I, White S, Cook J, Gilbert SJ, Heyes C, Bird G. Training social cognition: from imitation to theory of mind. Cognition. 2012;122(2):228–235. https://doi.org/10.1016/j.cognition.2011.11.004.

Uttal DH, Meadow NG, Tipton E, Hand LL, Alden AR, Warren C, Newcombe N. S. The malleability of spatial skills: a meta-analysis of training studies. Psychol Bull. 2013;139(2):352–402. https://doi.org/10.1037/a0028446.

van Tilburg WAP, Sedikides C, Wildschut T. The mnemonic muse: nostalgia fosters creativity through openness to experience. J Exper Soc Psychol. 2015;59:1–7. https://doi.org/10.1016/j.jesp.2015.02.002.

Westbrook L. Mental models: a theoretical overview and preliminary study. J Inf Sci. 2006;32(6):563–579. https://doi.org/10.1177/0165551506068134.

Appendix. Summary Image of Rationale and Approach

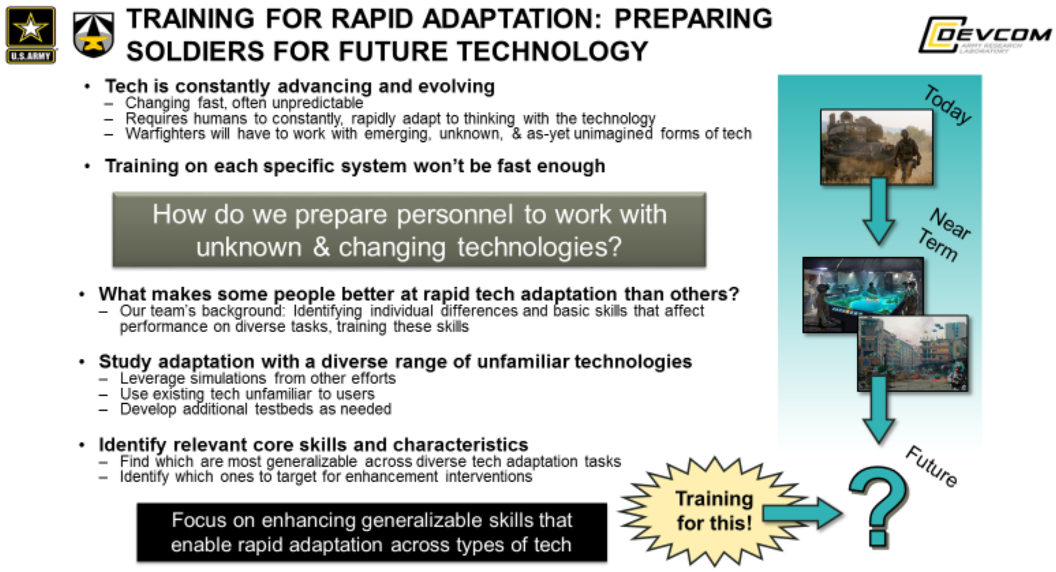

Fig. A-1 Summary image of rationale and approach

1 DEFENSE TECHNICAL
(PDF) INFORMATION CTR
DTIC OCA

1 DEVCOM ARL
(PDF) FCDD RLD DCI
TECH LIB

1 DEVCOM ARL
(PDF) FCDD RLH B
T DAVIS
BLDG 5400 RM C242
REDSTONE ARSENAL AL
35898-7290

1 DEVCOM ARL
(PDF) FCDD HSI
J THOMAS
6662 GUNNER CIRCLE
ABERDEEN PROVING
GROUND MD
21005-5201

1 USN ONR
(PDF) ONR CODE 341 J TANGNEY
875 N RANDOLPH STREET
BLDG 87
ARLINGTON VA 22203-1986

1 USA NSRDEC
(PDF) RDNS D D TAMILIO
10 GENERAL GREENE AVE
NATICK MA 01760-2642

1 OSD OUSD ATL
(PDF) HPT&B B PETRO
4800 MARK CENTER DRIVE
SUITE 17E08
ALEXANDRIA VA 22350

ABERDEEN PROVING GROUND

15 DEVCOM ARL
(PDF) FCDD RLH
J LANE
Y-S CHEN
P FRANASZCZUK
K MCDOWELL
FCDD RLH F
J GASTON
K OIE
FCDD RLH FA
B FILES
AW EVANS
G BOYKIN
FCDD RLH FB
J GARCIA (A)
H ROY
FCDD RLH FC
J TOURYAN (A)
K POLLARD
T ROHALY
FCDD RLH FD
A MARATHE