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ABSTRACT

Multigenerational Inequality

A growing literature provides evidence on multigenerational inequality – the extent to which socio-economic advantages persist across three or more generations. This chapter reviews its main findings and implications. Most studies find that inequality is more persistent than a naive iteration of conventional parent-child correlations would suggest. We discuss potential interpretations of this new "fact" related to (i) latent, (ii) non-Markovian or (iii) non-linear transmission processes, empirical strategies to discriminate between them, and the link between multigenerational and assortative associations.

JEL Classification: J62, J12

Keywords: multigenerational inequality, assortative mating, distant kins

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1 Introduction

Studies of social mobility often focus on two generations, measuring how one's education, income or other outcomes are associated with that of one's parents. But how persistent are socio-economic inequalities in the long run, across multiple generations? A naive extrapolation from conventional parent-child estimates would suggest that long-run persistence is low – that the influence of family background declines geometrically and washes out over three or four generations. However, a growing literature provides direct evidence on *multigenerational inequality*. This chapter reviews this evidence and its implications.

We first illustrate why multigenerational regression coefficients deviate from the iterated product of the corresponding parent-child coefficients (Section 2), even though the "iteration" of coefficients may appear natural in a regression framework. Indeed, this *iterated regression fallacy* has been a common source of misinterpretations in intergenerational research and other contexts. The reason why parent-child correlations may not be very informative about multigenerational persistence is that they measure only a descriptive rather than a structural relationship.

We then review recent empirical evidence on multigenerational inequality (Section 3). A robust pattern across studies is that inequality is more persistent than a naive iteration of the parent-child correlations would suggest. Put differently, the coefficient on grandparents in a child-parent-grandparent regression tends to be positive: grandparent status predicts child status, even conditional on parent status. However, this "excess persistence" partly reflects the omission of important characteristics of the parent generation; a particularly vital omission is the second parent.

Less clear is how this new empirical "fact" should be interpreted. We highlight three potential interpretations related to (i) latent, (ii) non-Markovian and (iii) non-linear transmission processes (Section 4). Some parental influences are inherently unobservable, and such latent processes could generate multigenerational persistence. Alternatively, perhaps "grandparents matter" in a causal sense, exerting an influence on their grandchildren that is distinct from parental influences. As a third possibility, transmission processes could be non-linear or vary across families. While non-linearities have been studied in other contexts, its multigenerational implications have received less consideration.

We also link this evidence to earlier work on sibling correlations, which suggests that parental characteristics such as schooling or income account only for a minor part of the family and community influences that siblings share (Björklund and Salvanes, 2011; Jäntti and Jenkins, 2014). Intuitively, as family background cannot be captured by one single variable, intergenerational associations may reflect only the "the tip of the iceberg" of family background effects (Björklund and Jäntti, 2012). We argue that multigenerational associations reflect this same insight, making those associations meaningful even if their absolute size remains limited.

One intriguing implication of strong multigenerational associations is that assortative mating must be strong, too (Section 5). Conventional measures of assortative mating imply rapid regression to the mean across generations, which would be at odds with high multigenerational correlations. Consequently, multigenerational studies not only shed light on the long-term persistence of inequality, but also offer novel insights into fundamental aspects of *inter*generational transmission, like the level of sorting within a population.

For brevity, this chapter omits many important questions. The stylised models we consider are "mechanical", abstracting from economic choices and behaviours. We do not address policy or normative questions, such as whether multigenerational correlations are "too high". Instead, this chapter focuses on basic empirical facts and their potential interpretations, which might inform future work. It is complementary to an earlier review by Anderson, Sheppard and Monden (2018). While they provide a systematic summary of multigenerational estimates, this chapter focuses on the interpretation of such estimates and relation to other measures of social mobility. Other insightful discussions of multigenerational mobility include Pfeffer (2014), Solon (2018) and Breen (2018), and some sections of this chapter draw on Stuhler (2012) and Blanden, Doepke and Stuhler (2023).

2 The Iterated Regression Fallacy

Our understanding of intergenerational processes has been shaped by theoretical and empirical research involving just two generations, parents and children (Mare 2011). It is therefore instructive to first consider why an extrapolation from the available parent-child evidence may not be very informative about the persistence of socio-economic status across multiple generations (in the "long run").

The degree of status persistence between *parents* and their children is often measured by the slope coefficient in a linear regression of outcome y in offspring generation t of family i on the parental outcome in generation $t-1$,

$$y_{it} = \alpha + \beta_{-1} y_{it-1} + \varepsilon_{it}. \tag{1}$$

For example, if y is the logarithm of income then β_{-1} captures the *intergenerational elasticity of income*; a high elasticity represents low mobility. For simplicity we assume below that β_{-1} remains constant across generations, but the arguments extend to non-stationary environments.

How does the coefficient from this Galtonian regression across two generations compare with the coefficient across three or more generations? The idea that the latter equals the square of the former, so that persistence declines geometrically, may appear as a natural consequence of regression: if β_{-1} captures to what degree deviations from the mean tend to be passed from parents to children then we might expect $(\beta_{-1})^2$ to represent their expected extent after being passed twice from parents to children, between grandparents and their grandchildren. Formally, we may use equation (1) to rewrite the grandparent-grandchild elasticity β_{-2} as

$$\beta_{-2} \equiv \frac{Cov(y_{it}, y_{it-2})}{Var(y_{it-2})} = \frac{Cov(\beta_{-1} y_{it-1} + \varepsilon_{it}, y_{it-2})}{Var(y_{it-2})} \stackrel{?}{=} (\beta_{-1})^2. \tag{2}$$

The fallacy is in the last step: while ε_{it} is by construction uncorrelated to y_{it-1}, it is not necessarily uncorrelated with grandparental status y_{it-2}. Intuitively, the coefficient β_{-1} in equation (1) captures only a statistical, not a structural association.[1]

This "*iterated regression fallacy*" (Stuhler, 2012), i.e. the belief that regression toward the mean between two periods implies iterated regression across multiple periods, is a common misconception. Bulmer (2003) describes how Francis Galton fell fault of it in his influential work on linear regression and Nesselroade, Stigler and Baltes (1980) discuss its prevalence in psychological research (using the label "expectation fallacy"). As discussed in the next section, a naive iteration of parent-child correlations tends instead to understate the extent of multigenerational inequality.

[1]Importantly, equation (2) may fail to hold even in a Markovian world, in which outcomes depend only on the previous generation (Mare, 2011). We illustrate this argument in Section 4.

3 Multigenerational Inequality

How persistent are socio-economic inequalities? A string of recent studies provide a new perspective on this question by tracking families over multiple generations. Spurred by the increased availability of suitable data, research on multigenerational mobility has surged nearly simultaneously in economics (e.g., Lindahl et al., 2015), sociology (Chan and Boliver 2013), demography (Mare 2011), and economic history (Dribe and Helgertz 2016). However, different studies emphasise different interpretations, a point to which we return in the next section. Anderson, Sheppard and Monden (2018) provide a systematic review of earlier studies, and is complementary to the more selective presentation here.

3.1 Measuring multigenerational inequality

Multigenerational evidence tends to be presented in one of two distinct forms. We may compare the relative size of inter- and multigenerational correlations, i.e. whether multigenerational correlations are larger or smaller than the naive iteration of parent-child correlations would suggest,

$$\beta_{-k} \lesseqgtr (\beta_{-1})^k \tag{3}$$

where β_{-k} is the multigenerational correlation between generation t and generation $t-k$, for $k>1$. Alternatively we may estimate a multivariate regression of the form

$$y_{it} = \alpha + \beta_p y_{it-1} + \beta_{gp} y_{it-2} + ... + \varepsilon_{it}. \tag{4}$$

and study the sign and magnitude of the slope coefficients on grandparents or earlier ancestors.[2] The distinction is just a presentational one: using the Frisch-Waugh-Lovell theorem, the coefficient β_{gp} in the three-generation regression (4) can be re-expressed as (see Braun and Stuhler, 2018)

$$\beta_{gp} = \frac{\beta_{-2} - (\beta_{-1})^2}{1-(\beta_{-1})^2}, \tag{5}$$

such that we have "excess persistence" in the sense of $\beta_{gp} > 0$ if and only if $\beta_{-2} > (\beta_{-1})^2$. Given this duality, there is a close link between studies providing bivariate estimates, as in (3), and those focusing on multivariate estimates, as in (4).

3.2 Multigenerational evidence

Until recently, little multigenerational evidence has been available. Hodge (1966) warns that mobility may not be well described by a first-order Markov process in which child outcomes depend only on the parent generation. Studying families over three generations in Wisconsin, Warren and Hauser (1997) show that the occupational status of grandparents is not very predictive of their grandchildren's status once father's education, occupation and earnings, and mother's education, are controlled for. However, their estimates are not very precise due to the limited size of their sample. Similarly, Erola and Moisio (2007) report that conditional on parents' *class* (see also Heath and Li 2024, published in the same

[2] One interesting observation is that the addition of grandparents or other ancestors often contributes little in an R^2 sense, even if the corresponding slope coefficients are large. We return to this observation in Section 4.5.

Table 1: Selected Multigenerational Studies

Study	Sample	Main outcomes	Excess persistence	Remarks
Warren and Hauser (1997)	US (Wisconsin)	Education, Occupation	No, cond. on parent characteristics	Conditioning tests
Lindahl et al. (2015)	Sweden (Malmö)	Education, Income	Yes, $\beta_{-k} > \beta^k$ and $\beta_{gp} > 0$	Link up to four generations for education
Adermon, Lindahl and Waldenström (2018)	Sweden	Wealth	Yes, $\beta_{gp} > 0$	Study bequests and wealth, earnings, education up to four generations
Braun and Stuhler (2018)	Germany	Education, Occupation	Yes, $\beta_{-k} > \beta^k$ and $\beta_{gp} > 0$	Latent factor model, conditioning tests, education up to four generations
Pfeffer and Killewald (2018)	US	Wealth	Yes, $\beta_{-k} > \beta^k$ and $\beta_{gp} > 0$	Study role of bequests, educational attainment, marriage, homeownership, and business ownership
Sheppard and Monden (2018)	21 countries (SHARE)	Education	Yes, $\beta_{gp} > 0$	Test for grandparent, contact and interaction effects
Neidhöfer and Stockhausen (2019)	US, UK and Germany	Education	Yes, $\beta_{-k} > \beta^k$ and $\beta_{gp} > 0$ (UK and Germany)	Conditioning tests, multigenerational trends, latent factor model
Colagrossi, d'Hombres and Schnepf (2020)	28 EU countries	Education, Occupation	Yes, $\beta_{-k} > \beta^k$ and $\beta_{gp} > 0$ (most countries)	Conditioning tests, latent factor model
Engzell, Mood and Jonsson (2020)	Sweden	Income	Unconditional $\beta_{gp} > 0$, conditional $\beta_{gp} \approx 0$	Conditioning tests, heterogeneity of multigenerational associations
Hällsten and Kolk (2020)	Sweden (Skellefteå and Umeå)	Education, Occupation, Wealth	Yes, $\beta_{-k} > \beta^k$ and $\beta_{gp} > 0$	Up to seven generations and 5^{th}-order cousins
Modalsli (2023)	Norway	Occupation, Income	Yes, $\beta_{-k} > \beta^k$ and $\beta_{gp} > 0$	Study contact effects, multigenerational trends
Li and Cao (2023)	China	Education	Yes, $\beta_{-k} > \beta^k$ and $\beta_{gp} > 0$	Conditioning tests, contact effects, multigenerational trends

Notes: Selected studies with multigenerational family links. "Conditioning tests" correspond to estimates of β_{gp} in equation (4) with different sets of parental controls.

volume as this chapter), the grandchildren's social class is nearly independent from the grandparents' class in Finland, while Chan and Boliver (2013) find a more robust conditional association in British data. See Hertel and Groh-Samberg (2014) for further discussion of these studies.

Lindahl et al. (2015) combine survey data from the Swedish "Malmö study" with administrative data to track earnings for three generations and educational attainment over four generations. They find that multigenerational persistence is much higher than would be predicted from the iteration of regression estimates for two generations, i.e. $\beta_{-k} > (\beta_{-1})^k$ and $\beta_{gp} > 0$ in the three-generation regression (4). The size of the coefficient on grandparents' (standardised) earnings is about one quarter of the corresponding coefficient on father's earnings, which is also the median ratio of β_{gp}/β_p across 40 research articles reviewed by Anderson, Sheppard and Monden (2018). The results by Lindahl et al. received much attention. Although restricted to one Swedish region, their data are of high quality and contain earnings. Moreover, their findings are at odds with a well-known prediction by Becker and Tomes (1986) that "*Almost all earnings advantages and disadvantages of ancestors are wiped out in three generations*".

Braun and Stuhler (2018) interpret multigenerational correlations in educational and occupational status in different German samples through the lens of a latent factor model (see Section 4.1). The implied parent–child correlation in "latent" advantages is about 0.6, nearly 50 percent larger than the parent-child correlation in years of schooling in their samples. Applying a similar approach on harmonised survey data, Neidhöfer and Stockhausen (2019) find slightly higher latent persistence around 0.7 for Germany and slightly lower persistence rates for the US and UK, while Colagrossi, d'Hombres and Schnepf (2020) estimate a mean rate of latent persistence of 0.66 in standardised educational outcomes across 28 European countries.

Similar patterns are found for other outcomes, such as wealth (see also Chapter 7 by Lersch, Longmuir and Schnitzlein). Using Swedish data, Adermon, Lindahl and Waldenström (2018) show that grandparents' wealth is predictive of grandchildren's wealth, above and beyond parent wealth. This pattern is even more pronounced in studies by Boserup, Kopczuk and Kreiner (2013) for Denmark and Pfeffer and Killewald (2018) for the US. While it could be partially explained by direct bequests from grand- to grandchildren that "skip a generation" (Mare, 2011), advantages associated with family wealth arise at an earlier age than such direct bequests would imply. Conditional on parental wealth, grandparents' wealth also predicts other outcomes of their grandchildren, such as education and home ownership (Pfeffer and Killewald, 2018) or school grades (Hällsten and Pfeffer, 2017).

Some recent studies are able to link more than "just" three generations. In particular, Hällsten and Kolk, 2020, link administrative data and parish records from Northern Sweden to track up to seven generations. The observation of such long data coverage would also allow researchers to estimate *trends* in multigenerational persistence. For example, Modalsli (2023) links up to five generations of data in Norway, and finds substantial differences in the strength of multigenerational persistence over time. As yet there exists little evidence on multigenerational correlations in developing countries, with Razzu and Wambile (2020), Kundu and Sen (2021) and Celhay and Gallegos (2025) as recent exceptions.

Most studies find that multigenerational correlations are larger than a naive iteration of parent-child estimates would suggest. This pattern appears robust across countries and different socio-economic outcomes. However, a substantial share of this "excess persistence" can be explained by the omission of the second parent, and studies that control for both maternal and paternal characteristics (e.g., Engzell, Mood and Jonsson, 2020) tend to find a much smaller and sometimes insignificant coefficient

β_{gp} in the child-parent-grandparent regression (4). There exists only limited evidence on whether multigenerational patterns vary across countries or groups.[3] Most importantly, there is no consensus yet on how those patterns should be interpreted: while some studies emphasise the role of "latent" transmission channels, others emphasise the causal influence of grandparents or the extended family. We discuss potential interpretations in Section 4.

One common issue in multigenerational studies is that the marginal distributions tend to be very different for distant ancestors. Educational attainment is often low, income rarely observed, and occupational classifications can be problematic if the share of farmers is high in older generations. Moreover, very different mechanisms can generate similar "vertical" transmission patterns (Cavalli-Sforza and Feldman, 1981), making it difficult to distinguish between competing models. One alternative explored in recent studies is to consider distant relatives in the "horizontal" dimension. Adermon, Lindahl and Palme (2021) measure "dynastic human capital" based on a broad set of kinships in the parent generation, including uncles and aunts, and show that it has a much stronger association with child education than conventional parental measures. Collado, Ortuño-Ortín and Stuhler (2023) show that a single transmission model with strong assortative mating (see Section 5) can fit both vertical and horizontal kinship correlations.

Finally, some studies provide *causal* evidence on multigenerational spillovers. For example, Bütikofer, Dalla-Zuanna and Salvanes (2022) show that economic shocks affect social mobility not only in directly affected generations, but also have indirect effects on mobility in the third generation. Using a simple theoretical model, Nybom and Stuhler (2014) show that even a single structural change may trigger transitional dynamics in mobility over several generations, which can be non-monotonic.

While this chapter focuses on studies that use *direct* family links across generations, it is also related to recent *name*-based evidence by Clark (2014), Barone and Mocetti (2021), Belloc et al. (2023) and others. Names are informative about multigenerational persistence for two distinct reasons. The more obvious one is that using names, we can link very distant generations, at least in a probabilistic sense. For example, Barone and Mocetti (2021) find that the average status of surnames correlates across five centuries, which suggests that some components of the transmission process must exhibit high persistence. The second, more subtle reason is that the regression of surname averages between two generations might tell us something about the intergenerational transmission process that is not visible from individual-level regressions (Clark 2014, Clark and Cummins 2014). We return to this observation in the next section.

4 Interpretations and Mechanisms

How should this multigenerational evidence be interpreted? While informative about the long-run persistence of socio-economic inequalities, it is not directly informative about the underlying mechanisms, and different theoretical models could generate similar multigenerational patterns. This section reviews three potential interpretations related to (i) latent, (ii) non-Markovian and (iii) non-linear

[3] Cross-country comparisons by GDIM (2018), Neidhöfer and Stockhausen (2019), Colagrossi, d'Hombres and Schnepf (2020) or Celhay and Gallegos (2025) do find such variation. Open questions for future research include whether cross-country (Blanden, 2013) or regional differences (see Chapter 15 by Marie Connolly and Catherine Haeck) in parent-child correlations are also reliable indicators of differences in multigenerational inequality.

transmission processes.[4]

4.1 Latent transmission processes

Some of the advantages that parents transmit to their children may be inherently unobservable, as has long been recognised in both the social sciences (e.g., Duncan 1969, Goldberger 1972, Becker and Tomes, 1979) and population genetics (Rice, Cloninger and Reich 1978, Cavalli-Sforza and Feldman 1981). Clark (2014) and Stuhler (2012) show that such "latent" transmission has also interesting implications for the pattern of multigenerational transmission

To understand the basic argument, consider a simplified one-parent one-offspring family structure, in which the transmission in generation t of family i is governed by

$$y_{it} = \rho e_{it} + u_{it} \tag{6}$$

$$e_{it} = \lambda e_{it-1} + v_{it}, \tag{7}$$

in which an observed outcome y depends on latent endowments e (according to *returns* ρ), which are partially transmitted within families (according to *transferability* λ), and where u and v are white-noise error terms representing market and endowment luck, uncorrelated with each other and past values. To simplify the presentation we drop the i subscript and assume that e and y are standardised with mean zero and variance one, such that the slopes ρ and λ can be interpreted as correlations. To make matters concrete assume that our outcome of interest is (log) income, and that e measures an individual's human capital, although the argument can be applied in other contexts. The parameter ρ then measures the fraction of income that is explained by an individual's own human capital, as opposed to factors or events outside of individual control, such as market luck or market-level shocks; and $\rho = 1$ would imply that income differences are fully explained by an individuals' own characteristics.

Given this model, the intergenerational elasticity of income equals

$$\begin{aligned}\beta_{-1} &= Cov(y_t, y_{t-1}) \\ &= \rho^2 \lambda,\end{aligned} \tag{8}$$

and the elasticity across three generations equals

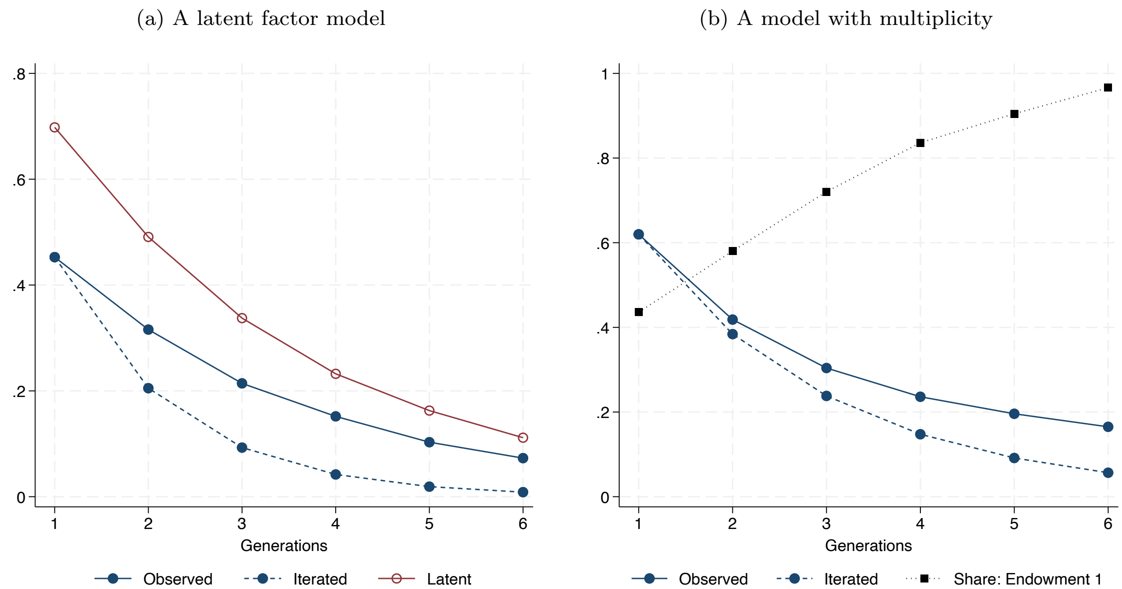
$$\begin{aligned}\beta_{-2} &= Cov(y_t, y_{t-2}) \\ &= \rho^2 \lambda^2.\end{aligned} \tag{9}$$

The extrapolation error from the iteration of the parent-child elasticity equals

$$\begin{aligned}\Delta &= (\beta_{-1})^2 - \beta_{-2} \\ &= \left(\rho^2 - 1\right) \rho^2 \lambda^2,\end{aligned} \tag{10}$$

[4] The presentation in this section draws and extends on Stuhler (2012). See also Lundberg (2020), who shows that different theoretical processes could explain the relative size of sibling and cousin correlations. We focus on purely "mechanical" transmission models, which can however be viewed as the reduced form of behavioural models (see Goldberger, 1989, and Lindahl, 2024). The interpretations reviewed here are not exhaustive; for example, Zylberberg (2013) considers a model in which dynasties move across careers, while Hertel and Groh-Samberg (2014) discuss the role of racial or ethnic segregation.

Figure 1: Multigenerational correlations in different models



Notes: Simulated data with n=10,000 observations. Panel (a) corresponds to the latent factor model with returns $\rho = 0.8$ and transferability $\lambda = 0.7$. The solid blue (red) line corresponds to the implied correlation in the observed outcome y (latent endowment e). The dashed line represents the *predicted* correlation based on the iteration of the parent-child correlation. Panel (b) corresponds to the multiplicity model with two endowments and $\rho_1^2 = 0.3$, $\rho_2^2 = 0.7$, $\lambda_1 = 0.9$ and $\lambda_2 = 0.5$. The black dashed line corresponds to the share of the correlation in y that is explained by the first endowment.

which is negative if $0 < \rho < 1$, that is as long as income is not perfectly determined by human capital.

Figure 1a provides a numerical example from this model, assuming $\rho = 0.8$ and $\lambda = 0.7$, and implying an intergenerational correlation of $\beta_{-1} = \rho^2\lambda \approx 0.45$.[5] A naive iteration of this parent-child correlation across multiple generations would imply rapid regression to the mean (dashed line); after only three generations, the iterated correlation falls below 0.1, such that the distribution of income among ancestors explains less than one percent of the variance in their descendants' income. But the *actual* correlation in income in this model decays much more slowly (solid blue line), falling below 0.1 after only six generations. The reason is the strong transmission of human capital (red line), which serves as the actual state variable in this model.

The key idea underlying this "latent factor model" is that the true transmission mechanisms are distinct from the status y observed by the researcher.[6] However, the representation of this idea in equations (6) and (7) is sufficiently generic to nest several distinct interpretations, with different implications. One possible interpretation is that y corresponds in fact to the "true" socio-economic status of an individual, but that status is transmitted not directly but indirectly via other pathways. For example, income y may be a good proxy for status, but parents might transmit human capital e rather than income to their children. In this interpretation, β_{-1} is in fact a truthful measure of status persistence between one generation and the next – it is just not very informative about persistence in the long run.

[5]The distributions u and v are chosen such that e and y are normally distributed with mean zero and variance one.

[6]The extrapolation error Δ will be particularly large when ρ is small, i.e. when the observable outcome y is not a good proxy for the latent endowments e. The gap between inter- and multigenerational correlations should therefore be particularly large when considering outcomes that are hard to measure, such as non-cognitive skills (e.g., Anger and Schnitzlein, 2017, and Kröger, Palacios-Abad and Radl, 2024).

Alternatively, we may assume that y is only a coarse proxy of socio-economic status, while e is the "true" or "generalised socio-economic status" of a person (as in Clark, 2014). For example, y may be short-run income, while e may represent a broader measure of socio-economic success. In this interpretation, β_{-1} is not only an inappropriate measure of multigenerational persistence; it is not even a good measure of the *inter*generational persistence of status differences from parents to their children (which would instead be captured by the red line in Figure 1a). Measurement error in the outcome y would be one important special case (see Solon 2014, Ferrie, Massey and Rothbaum 2021 and Nybom, 2024, published in the same volume as this chapter).

The basic proposition underlying the latent factor model is intuitive, and also consistent with earlier insights from the literature. In particular, it is consistent with the argument that sibling correlations are a more comprehensive measure of family background effects than intergenerational correlations, as they capture the influence of all the advantages that siblings share, not only the advantages encapsulated by parental income or education (Björklund and Salvanes, 2011). More generally, it is consistent with the argument that intergenerational correlations just measure the "tip of the iceberg" of family background effects (Björklund and Jäntti, 2012). However, not all models with latent transmission mechanisms generate high multigenerational persistence. In particular, the Becker-Tomes model in which child outcomes y also depend on parental income can produce either high or low multigenerational persistence (in the sense of $\beta_{-k} \lesseqgtr (\beta_{-1})^k$), depending on parameter values.[7]

4.2 Non-Markovian and extended-family processes

A second possibility is that intergenerational transmission deviates from a Markovian process, in that grandparents or other ancestors have an independent influence over and above the influence of parents. This possibility has already been considered by Warren and Hauser (1997), but the role of the wider family has received renewed attention after Mare (2011) published his eloquent criticism of the "two-generation paradigm" in intergenerational research (e.g., Chan and Boliver 2013, Hertel and Groh-Samberg 2014, Ferrie, Massey and Rothbaum 2021).

For illustration, assume that offspring human capital depends on both parents and grandparents,

$$y_t = \gamma_p y_{t-1} + \gamma_{gp} y_{t-2} + v_t, \tag{11}$$

where v_t is a white-noise error term assumed to be uncorrelated to the outcomes of parents or earlier ancestors. Note that compared to the descriptive associations captured by equation (4), we chose different symbols for the slope coefficients to indicate that equation (11) has a *structural* interpretation. Of course, if this "grandparent-effects" model is indeed the right model then the coefficients would coincide ($\beta_p = \gamma_p$ and $\beta_{gp} = \gamma_{gp}$), and we would observe "excess persistence" ($\Delta < 0$) iff $\gamma_{gp} > 0$.

Why might grandparents have an independent influence on their grandchildren? Mare (2011), Chan and Boliver (2013), Hertel and Groh-Samberg (2014) and Solon (2014) discuss potential mechanisms. Some of these mechanisms require overlapping lifespans or direct contact, such as when grandparents help in the upbringing of their grandchildren (Been et al. 2022), encourage or pay for educational investments, or transfer wealth. Other mechanisms do not: grandchildren may still benefit from the

[7] The model will tend to produce low multigenerational correlations (i.e., $\Delta < 0$) if parental income has a strong direct effect on child outcomes (Stuhler, 2012); moreover, $\Delta < 0$ holds with certainty in simplified versions of the Becker-Tomes model that abstract from the stochastic nature of the relation between income y and human capital e (Solon, 2014).

former contacts or reputation of their deceased grandparents, or may consider them as reference points guiding their own behaviour (Hertel and Groh-Samberg, 2014).

More generally, other members of the extended family may affect child outcomes. For example, Erola et al. (2018) find that in both US and Finnish data, aunts and uncles are better predictors of child education and earnings than grandparents, conditional on parent status. They note that this observation could be consistent with a model in which extended family members help with educational investments, provide access to educational opportunities and jobs, or serve as role models. And while equation (7) assumes linear effects, a more realistic model might account for interactions between different family members (e.g., the extended family might compensate for a lack of resources in the nuclear family, see Jæger 2012 or Erola and Kilpi-Jakonen, 2017), the overlap in lifespans, or the size of the extended family network (Lehti, Erola and Tanskanen, 2019).

4.3 Non-linear transmission processes and multiplicity

A third important reason why multigenerational correlations may decay less rapidly than iterations of the parent-child correlation are non-linearities and other forms of heterogeneity in the transmission processes. To see this, consider a transmission process with multiple transmission pathways ("multiplicity"). Specifically, we introduce a second endowment into the latent factor model,

$$y_t = \rho_1 e_{1t} + \rho_2 e_{2t} + u_t \tag{12}$$

$$e_{1t} = \lambda_1 e_{1,t-1} + v_{1t} \tag{13}$$

$$e_{2t} = \lambda_2 e_{2,t-1} + v_{2t}, \tag{14}$$

assuming that the two endowments are inherited from parents according to transferability λ_1 and λ_2. For simplicity, assume that the noise terms v_{1t} and v_{2t} are uncorrelated, such that $Cov(e_{1t}, e_{2t}) = 0$ $\forall$ t, and that both endowments affect income ($0 < \rho_1 < 1$ and $0 < \rho_2 < 1$). The parent-child and grandparent-grandchild correlations then equal

$$\beta_{-1} = \rho_1^2 \lambda_1 + \rho_2^2 \lambda_2$$
$$\beta_{-2} = \rho_1^2 \lambda_1^2 + \rho_2^2 \lambda_2^2$$
$$\ldots$$

and so on. In the special case in which incomes are *perfectly* determined by individual endowments, such that $\rho_1^2 + \rho_2^2 = 1$ and $Var(u_t) = 0$, the extrapolation error from the iteration of the parent-child correlation can be written as (Stuhler, 2012)

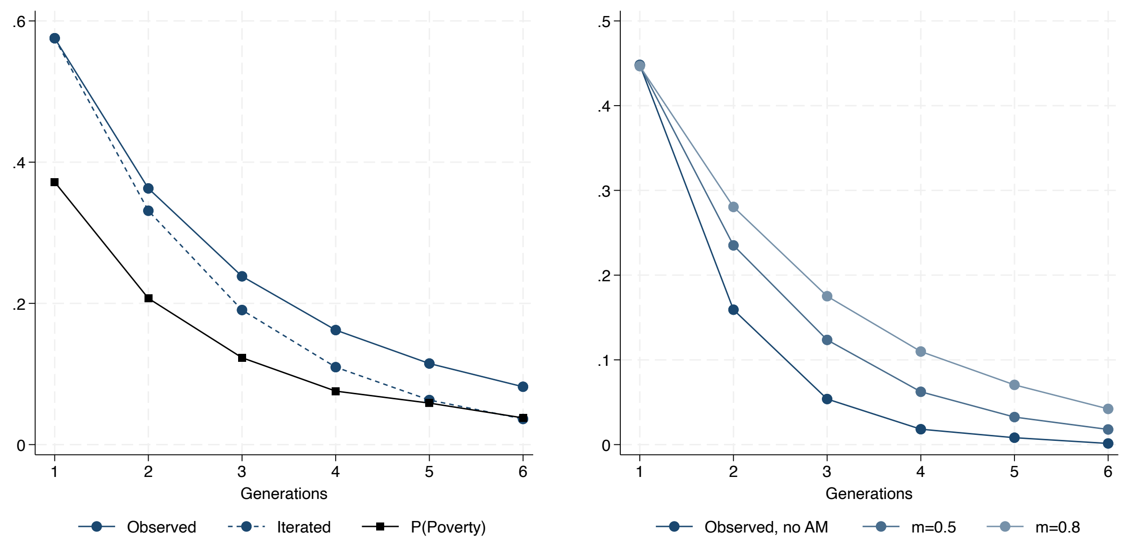
$$\Delta = \rho_1^2(\rho_1^2 - 1)(\lambda_1 - \lambda_2)^2, \tag{15}$$

which is negative for $\lambda_1 \neq \lambda_2$. This result can be understood as the application of Jensen's inequality: the square of the average transferability across endowments is smaller than the average of their square. Inequalities therefore decay more slowly if intergenerational income persistence stems from multiple causal pathways with differing rates of persistence.

Figure 1b provides a numerical example. As in the latent factor model, multigenerational correl-

Figure 2: Multigenerational correlations in different models (continued)

(a) A non-linear model with "poverty traps" (b) A latent factor model with assortative mating



Notes: Simulated data. Panel (a) corresponds to the model in equation (16) with $\gamma_1 = 0.9$, $\gamma_2 = 0.2$ and $\underline{y} = -0.3$. The solid black line corresponds to the persistence in poverty ($y < \underline{y}$). Panel (b) reports the correlations in the observed outcome y in a latent factor model with assortative mating (see Section 5), assuming $\rho = 0.8$, $\widetilde{\lambda} = 0.7$ and $m = \{0, 0.5, 0.8\}$.

ations (solid blue line) decay more slowly than an iteration of parent-child correlations (dashed blue line) would suggest. Moreover, the more transferable trait explains an increasing share of the long-run persistence in income (dotted line). One interesting implication is that *multi*generational persistence might reflect factors that are less important in explaining *inter*generational persistence; in our illustration, endowment e_1 contributes less to parent-child transmission than endowment e_2, but causes most of the multigenerational persistence. For example, racial segregation could be an important factor contributing to multigenerational persistence (Hertel and Groh-Samberg 2014, Margo 2016).

Similar implications arise with other forms of heterogeneity, such as non-linearities in the transmission process, as can be generated by neighbourhood effects or "poverty traps" (see Durlauf, 1994, and Nolan, 2024. For a simple illustration, assume there is modest transmission in the upper parts of the income distribution but high persistence in the bottom below some threshold $\underline{y}$, i.e.

$$y_t = \gamma_1 I(y_{t-1} < \underline{y})\left(y_{t-1} - \underline{y}\right) + \gamma_2 I(y_{t-1} \geq \underline{y})\left(y_{t-1} - \underline{y}\right) + u_t \tag{16}$$

where $\gamma_1 > \gamma_2$. Figure 2a provides a numerical example; we again find excess persistence in the form of $\Delta < 0$ in multigenerational correlations (blue solid line) compared to the prediction based on iterated parent-child correlations (dashed line). The probability to remain poor, in the sense of $y < \underline{y}$, decays slowly as well (black line).

The observation of high multigenerational correlations may therefore be a consequence of our tendency to ignore non-linearities and heterogeneity in the parent-child transmission process. But while such non-linearities have received much consideration in other contexts, its implications for multigenerational transmission have received less attention. Important recent exceptions are Bingley and Cappellari (2019), who note that the strength of transmission may vary systematically across families or different groups, Colagrossi et al. (2020), who note that such heterogeneity would affect the relative size of intergenerational and sibling correlations, and Benhabib, Bisin and Fernholz (2022), who show that a model with permanent heterogeneity in wealth returns can match the wealth distribution in both the short- and long-run.

4.4 Testing theories of multigenerational transmission

Very different mechanisms could therefore explain similar multigenerational patterns. Indeed, different fields have emphasised different interpretations. The latent-factor interpretation has been popular in economics (e.g., Clark 2014, Braun and Stuhler, 2018, Colagrossi, d'Hombres and Schnepf 2020). The grandparent-effect interpretation has received particular interest in demography, after Mare (2011, 2014) called attention to the role of the wider family. Both interpretations are found in sociology (Chan and Boliver, 2013; Engzell, Mood and Jonsson, 2020), while the implications of non-linear transmission for multigenerational mobility have received little attention in any field.

How can we then distinguish between these distinct interpretations? First, the observation of multigenerational persistence as such does not point to any particular theory. In particular, the finding that $\beta_{gp} > 0$ when estimating equation (4) should not be interpreted as favouring the grandparent-effect interpretation. As follows from (5), *any* process that generates high multigenerational persistence in the sense of $\beta_{-2} > (\beta_{-1})^2$ will also generate a positive grandparent coefficient, and vice versa. See also Lundberg (2020), who makes a similar point regarding the observation that cousin correlations tend to be larger than the square of the sibling correlation.

Researchers therefore need more specific evidence to distinguish between different candidate models. One testable implication of the latent factor model is that the coefficient β_{gp} should be sensitive to which parental characteristics are controlled for.[8] Warren and Hauser (1997) show that after conditioning on multiple parental characteristics, the occupational status of grandparents is not predictive of child status. Many recent studies report similar "conditioning tests" (see Table 1), typically finding that β_{gp} shrinks but remains positive after controlling for a wide set of parental characteristics (Sheppard and Monden, 2018). Such residual associations are still consistent with a latent factor model, as relevant characteristics might be missing in the data at hand, or be fundamentally unobservable.

Indeed, the more relevant question may be by *how much* β_{gp} declines when controlling better for parental characteristics, rather than whether β_{gp} remains positive. Using rich data from Sweden, Engzell, Mood and Jonsson (2020) show that even models that control for both parents' education, earnings, occupation, and wealth may still suffer from bias from the omission of relevant parental characteristics.[9] Moreover, while conditioning tests suggest that "grandparent effects" largely reflect omitted parental variables, Breen (2018) notes that these tests are subject to interpretative issues, too.[10]

[8] See also a recent strand of the literature that combines multiple proxy measures of parental status to explain child outcomes (Vosters and Nybom 2017, Blundell and Risa 2018, Hsu 2021 or Eshaghnia et al. 2021), or the literature on inequality of opportunity that often considers a wide set of "circumstances" (Brunori, Ferreira and Peragine 2013, Brunori, Hufe and Mahler 2022).

[9] Related, Modalsli and Vosters (2022) show that measurement in parent income may generate a spurious grandparent coefficient, even if a long-term average of parental income is controlled for.

[10] Breen (2018) shows that *partial* conditioning for some but not all relevant characteristics of the parent generation may not always reduce bias. Using the language of causal graphs, the issue is that parental status might not only be a "mediator" for the effect of grandparent on child status, but also a "collider" that is affected by other causal factors

One obvious source of omitted variable bias is the omission of one of the parents: the coefficient β_{gp} on grandparent's status tends to be smaller when controlling for *both* paternal and maternal characteristics. Braun and Stuhler (2018) show that in German samples, the coefficient on grandfather's status declines strongly once we condition on the corresponding status of the mother; indeed, Neidhöfer and Stockhausen (2019) and Engzell, Mood and Jonsson (2020) find that the coefficient can become negligible once both parents are accounted for. Detailed conditioning tests are also provided by Chiang and Park (2015), Fiel (2019) or Sheppard and Monden (2018).

Another interesting test is whether the association between grandparent and child status varies with the extent of contact between them. In a systematic review of the literature, Anderson, Sheppard and Monden (2018) find that the coefficient β_{gp} does not appear to vary systematically with the likelihood of contact between grandparent and grandchild (see also Helgertz and Dribe, 2022). However, Zeng and Xie (2014), Knigge (2016) and Song and Mare (2019) are notable exceptions, and a direct effect of grandparents on their grandchildren is also possible through means that do not require contact, such as financial transfers (Hällsten and Pfeffer, 2017).

A third strategy is to estimate persistence at an aggregate rather than individual level. For example, the parameter λ in the latent factor model could be estimated by averaging y across multiple relatives, to then estimate the regression to the mean on the surname level. With this motivation in mind, Clark (2014), Clark and Cummins (2014) and related studies document strikingly strong persistence of socio-economic status at the *surname* level, across many different countries and time periods. While the precise interpretation of name-based estimators is contested (e.g. Torche and Corvalan 2018, Santavirta and Stuhler 2021), they might prove useful to discriminate between competing models of multigenerational inequality. For example, Belloc et al. (2023) find that even great-grandparents' wealth is still predictive of child wealth, conditional on parents' and grandparents' wealth, and note that this pattern could be consistent with a latent factor model.

A fourth strategy is to confront competing transmission models with a wider set of kinship correlations. The "right" model should explain not only the relation between multi- and intergenerational correlations, but also their relation to sibling and many other type of kinship correlations. For example, Collado, Ortuño-Ortín and Stuhler (2023), show that a generalised latent factor model can provide a good fit to a wide set of 141 distinct kinship moments in Swedish data. One interesting question is whether non-linear or non-Markovian models could provide a similarly good fit, or explain status correlations between very distant ancestors (Barone and Mocetti, 2021).

These obstacles in the interpretation of multigenerational correlations are of course the same obstacles that limit our understanding of social mobility more generally. Statistical associations are difficult to map to mechanisms, and while robust causal evidence exists for certain pathways, most of the statistical associations remain unaccounted for (Björklund and Jäntti, 2020). Moreover, distinguishing between the models considered in Section 4 is only a first challenge, as those stylised models are not precise about the *specific* mechanisms and behavioural patterns that matter, or how policies and institutions would affect them.

Still, the recent multigenerational evidence is not "toothless", as it reduces the range of permissible models. For example, the standard implication of the Becker-Tomes model for β_{gp} to be negative (see Section 4.1) is rejected by most papers. Related, Collado, Ortuño-Ortín and Stuhler (2023) show that a purely genetic model with phenotypic assortment could not fit the kinship pattern in educational

influencing both parent and child status (such as neighbourhood effects).

Table 2: On the explanatory power of multigenerational associations

	Dependent variable: Child status y					
	(1)	(2)	(3)	(4)	(5)	(6)
Parent's y	0.450***	0.389***	–	0.392***	–	0.310***
	(0.004)	(0.004)		(0.004)		(0.004)
Grandparent's y	–	0.138***	–	–	–	–
		(0.004)				
Sibling's y	–	–	0.306***	0.131***	0.458***	0.318***
			(0.004)	(0.004)	(0.004)	(0.004)
R^2	0.204	0.219	0.095	0.218	0.210	0.286

Notes: Simulated data from the latent factor model in equations (6) and (7) with returns $\rho = 0.8$ and transferability $\lambda = 0.7$ over three generations (n=50,000). For columns (3) and (4), the noise term u is uncorrelated between siblings. For columns (5) and (6), u is drawn from a joint normal distribution with correlation 0.4 between siblings.

advantages. And while there is no consensus yet on the underlying mechanisms, multigenerational estimates are directly informative about the extent of status persistence in the long run – thereby providing novel insights about an important dimension of inequality.

4.5 Does this matter? The R^2 controversy

Do multigenerational associations "matter" in a quantitative sense? One frequent observation is that conditional on parents, other ancestors do not add much to the regression R^2 – even if the corresponding slope coefficients appear sizeable. For example, Pfeffer and Killewald (2018) report that switching from a two- to a three-generations regression, the R^2 increases only mildly (from 0.146 and 0.160), even though the coefficient on the grandparents' wealth is nearly half as large as the coefficient on the parents' wealth. Erola and Moisio (2007) make a similar observation in Finnish data. This low contribution in a R^2 sense is also a key point in an interesting recent debate between Björklund, Hederos and Jäntti (2022) and Adermon, Lindahl and Palme (2022).

To provide an illustration, we generate simulated data based on the latent factor model given by (6) and (7) and the same parameters as in Figure 1 ($\lambda = 0.7$ and $\rho = 0.8$). Table 2 reports regression estimates from this simulated data. Column (1) reports estimates of the intergenerational coefficient β_{-1}, which according to equation (8) equals $\beta_{-1} = \rho^2\lambda$. In column (2) we add the grandparent status to the model. But while the coefficient on grandparents is sizeable, the regression R^2 hardly increases. Hence the conundrum: are deviations from the "iterated" parent-child regression (Section 2) important, as indicated by the regression slopes, or negligible, as seemingly implied by the R^2?

The answer depends on *why* multigenerational associations exist. While the R^2 differs little between columns (1) and (2), the significant coefficient on grandparents signals that the transmission process deviates from the simple parent-child regression. And in our chosen example, that deviation turns out to be important: advantages are transmitted at a *much* higher rate than the parent-child correlation suggests ($\lambda = 0.7$ vs. $\beta \approx 0.45$), and the multigenerational implications differ substantially (Figure 1a). The observation of independent multigenerational associations can therefore be meaningful, even if the regression R^2 moves little.

It is instructive to compare multigenerational to *sibling correlations*, as an alternative measure of family influences. We simulate two children per parent, initially assuming that the errors u and v in equations (6) and (7) are uncorrelated between siblings. As shown in column (3) of Table 2, the implied sibling correlation (0.31) is much larger than the square of the parent-child correlation ($0.45^2 = 0.20$), even though the addition of siblings does not add much to the R^2 in a parent-child regression (cf. columns 1 and 4). The "excess persistence" found in multigenerational studies (column 2) and sibling correlations (cf. columns 1 and 3) could therefore reflect similar mechanisms.

However, the measures are not interchangeable: sibling correlations are a broad measure of family background that also capture environmental influences that siblings share, such as neighbourhood or peer effects (Björklund and Salvanes, 2011, Jäntti and Jenkins 2014), while multigenerational correlations capture the effect of ancestry in a narrow sense. To illustrate this point, columns (5) and (6) replicate the regressions from columns (3) and (4) but allow for shared influences between siblings (see table notes). This increases the sibling correlation further (cf. columns 3 and 5), and the R^2 in a regression with parents *and* siblings is now substantially larger as compared to the simple parent-child regression (cf. columns 1 and 6), as is the case in actual applications.

5 Assortative Matching

The observation of significant multigenerational correlations also has implications for the *assortative* matching between spouses. To see this, extend the latent factor model as given by equations (6) and (7) to a two-parent setting (see also Braun and Stuhler, 2018), assuming that an offspring's endowment depends on the average of the father's and mother's endowment,

$$e_t = \tilde{\lambda}\frac{e^m_{t-1} + e^p_{t-1}}{2} + v_t, \tag{17}$$

where the m and p superscripts denote maternal and paternal variables, respectively. Normalising y and e to one, the parent-child correlation in y between a child and *one* parent is now given by

$$\beta_{-1} = \rho^2\tilde{\lambda}\frac{1+m}{2}, \tag{18}$$

where $m = Corr\left(e^m_{i,t-1}, e^p_{i,t-1}\right)$ measures the extent of assortative matching among parents. The multigenerational correlations with earlier ancestors are similarly given by

$$\beta_{-k} = \rho^2\tilde{\lambda}^k\left(\frac{1+m}{2}\right)^k \tag{19}$$

for $k > 1$. Because β_{-k} depends on $\left(\frac{1+m}{2}\right)^k$, multigenerational correlations will decay quickly if assortative matching is weak – even if parental endowments were transmitted perfectly.[11]

Figure 2b provides a numerical example with $\rho = 0.8$ and $\tilde{\lambda} = 0.7$ and three different assortative correlations, with $m = 0$ (no assortative matching), $m = 0.5$ (a typical value for the spousal years of schooling, Fernandez, Guner and Knowles, 2005) and $m = 0.8$. The example illustrates that high multigenerational correlations are possible only if assortative matching is very strong, a point that is also discussed by Clark (2014). Indeed, conventional assortative measures may understate sorting

[11] Here we consider the correlations with a single ancestor. Some studies average over all ancestors in a generation, thereby abstracting from sorting. For example, in the model considered here the correlation between the child and parents' average status would be $\rho^2\tilde{\lambda}$ and thus not depend on m.

for the same reasons that parent-child correlations understate intergenerational transmission: the similarity of spouses in observable characteristics, such as years of schooling, may not capture their resemblance in unobserved determinants of child outcomes. Collado, Ortuño-Ortín and Stuhler (2023) estimate that in Sweden, the spousal correlation in such latent determinants must be around 0.75, or more than 50 percent larger than the spousal correlation in years of schooling, to explain the correlation patterns between distant in-laws.

6 Conclusions

This chapter provided an overview of the fast-growing literature on multigenerational inequality. Using data across three or more generations, recent studies show that socio-economic inequality tends to be more persistent than a naive extrapolation from conventional parent-child measures would suggest. However, very distinct interpretations of that new "fact" are possible. Its significance might lie less in the magnitude of multigenerational associations per se, as adding earlier ancestors often contributes little to the overall explanatory power of parent-child models. More importantly, multigenerational associations tell us something novel about the nature of intergenerational processes.

One plausible interpretation is that parent-child transmission – and assortative mating – must be much stronger than what conventional measures capture. But the chapter also reviews alternative interpretations, related to "grandparent effects" or non-linearities in the transmission process, and more work is needed to distinguish between competing models. One exciting aspect is that this work is happening simultaneously in multiple fields of the social sciences, connecting different strands of research that otherwise tend to progress in isolation.

To retain focus, we passed over many important aspects. Empirically, one major concern is sample selection regarding the coverage of different generations, the coverage of migrants, or the age at which the outcome of interest can be observed. Conceptually, some studies rely on steady-state assumptions that are less plausible when comparing many generations (Nybom and Stuhler, 2019), and most abstract from demographic processes and differences in fertility (Song, 2021). A more explicit consideration of these aspects could be fruitful for future work.

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